Incorporation of micro-level analysis in strategic urban transport modelling: with a case study of the Greater Beijing

This thesis is submitted
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by

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Bin Deng

Abstract

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Many developing countries and regions are suffering from severe urban transport problems arising from accidents, congestion, air pollution, rising carbon intensity, and chronic under-funding of infrastructure and services. The problems make those cities the most polluted and often the least liveable. Strategic transport modelling has been recognised as an effective approach for developing and testing policy options, especially where it is integrated with land use planning and urban design. However, in most developing-country cities strategic transport modelling has been out of reach for practical policy use because of its sophisticated data and skill requirements, which currently imply unaffordable high costs and long durations for model development. This means that strategic urban transport modelling is the least available where it is needed most urgently. Meanwhile, the spread of smart data in mapping and urban activity monitoring has often been just as rapid in developing countries as in the developed. This has triggered new approaches in micro-level analyses of transport networks, personal movements and vehicles. In the most advanced cases, the new analyses have started to influence strategic modelling.

The main hypothesis of this dissertation is that an incorporation of the micro-level smart data and analyses in strategic urban transport modelling will make it feasible to establish a sufficiently robust strategic transport model for evidence-based policy analysis with cost, time and skill thresholds that are close to being affordable in developing country cities. In order to test this main hypothesis, a number of novel model development tasks have been carried out which contribute to the field of applied urban modelling. This new approach aims to contribute to the transformation of the prevailing modus operandi where model development could not start in earnest until extensive data collection and skills training have been completed to a situation where a sufficiently robust model can be established cheaply and quickly to support on-going and incremental refinements.

More specifically, new modelling tools have been developed as part of this dissertation using sparse GPS taxi traces to identify slow-moving and stopping traffic hotspots using an extended density-based spatial clustering algorithm that is tolerant of significant data noise, and to estimate congested road speeds (which used to be very costly and time-consuming to obtain if

at all). The micro-level network, congested speeds and insights into the nature of the congested traffic have been incorporated into a MEPLAN-based strategic transport model interacting with a MEPLAN-based land use and travel demand model. This means that the strategic economic, social and environmental impacts of transport interventions can be tested in a robust way through accounting for the interactions among transport, land-use and background social-technical trends. A new approach to establish the medium to long term visions for alternative travel demand management and transport investment scenarios has been tested using this model.

The methods and algorithms have been tested in a case study of the Greater Beijing region, which consists of the municipalities of Beijing and Tianjin together with the surrounding areas in the province of Hebei. The government's data regulations of restricting overseas studies to using only publicly available data sources have made the case study ideal for testing the new approach. The potential of the new strategic urban transport model has been tested through a wide range of policy scenarios. The results suggest that the new approach developed in this dissertation has made it not only cheaper and faster to develop a robust model, but could also potentially fill a gap in the lack of medium to long term perspectives regarding major road and metro investments over the next two decades. Such analyses could be of critical importance in improving the performance of the transport system in terms of safety, economic efficiency, air quality and carbon reduction given the long lead times to plan and deliver transport infrastructure investments.

KEY WORDS: Strategic transport modelling; Taxi GPS data; Transport policy intervention; Scenario tests; Greater Beijing Region; Data mining; Urban modelling.

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1. Introduction

From São Paulo to Mexico City, from Cairo to Lagos and from Delhi to Beijing, emerging regions and countries are encountering many similar transport problems to those of the rich world in the recent past: rise of motorised travel, congestion, pollution, air quality, carbon emission and so on (UN-Habitat, 2016). These transport disorders can offset the benefit of urban expansion and economic agglomeration, especially when the regulatory framework is not capable of addressing the rapid-rising travel demand from citizens who live, work and move across urban regions.

Where the developing world could to some extent learn from the experiences of the developed countries, there are other new challenges that call for innovation in urban and transport modelling. The challenges include much more rapid urban expansion, deeper lack of sound data, and worse scarcity of resources. Meanwhile, the existing methods are not sufficient for supporting medium-to-long-term development of those cities.

In the developed countries, strategic transport modelling (i.e. computer simulation of the interactions between transport demand and supply over the medium to the long term e.g. 10-20 years) has been recognised as an effective approach for evaluating policy options regarding land-use plan and infrastructure development. Based on the best available evidence, it provides policymakers and regulators with estimates for the outcomes (e.g. level of congestion and amount of pollutant emission) from different developing scenarios. But in most of the emerging cities and regions, strategic transport models are still out of reach due to (1) the insufficiency of resources including capital, quality data and skilled personnel; and consequently (2) the unaffordable high price and unbearable long duration for developing such models. These have led to low accessibility of strategic transport modelling where there is the most urgent need.

A possible pathway to address this rising need has been emerging recently, with the widespread applications of GPS (Global Positioning System) data (e.g. trajectory data collected by GPS-equipped devices). The conventional input data sets required for establishing transport models, which are used to be costly to collect and time-consuming to process, can now be derived promptly from new measures using GPS data. These potent GPS-related methods can potentially influence strategic transport modelling, making it more achievable for a sufficiently robust strategic transport model, which can be used to provide policy assessments with cost, time and skill thresholds that are close to being affordable in developing countries.

Therefore, in this dissertation we aim to establish a strategic transport model as part of the integrated land use and transport model in an efficient and less expensive way by introducing the application of GPS data and analyses. For this purpose, two main tasks have been specified as follows:

(1) To establish a strategic transport model, with incorporation of GPS data and analyses and in consideration of data availability and resource scarcity.

(2) To provide medium-to-long-term visions for alternative scenarios of transport policies, based on the test results from this model.

Task (1) is aimed at the transformation from prevailing modus operandi where model development could not start in earnest until the completion of extensive data collection and delicate skills training, to a situation where a sufficiently robust model can be established affordably and agilely in order to support on-going and incremental refinements. Here the development of the strategic transport model follows the traditional four-step approach and the well-established methodologies. Through the literature of the studies, we identify the estimation of congested link speeds using GPS data as a feasible way to assist the model development. The resulting speed results are fed into the choice model to replace those conventionally generated through an iterative progress with stiff constraints on validation and calibration. We also explore the identification of hotspots of non-moving and slow-moving GPS data points; which results can be used in comparison against our local knowledge to investigate the characteristics of the source GPS data in order to assure the quality of the output link speeds.

The developed model interacts with a land use and travel demand model (Rong, 2016), with further linkage to a medium-to-long-term spatial economic and land use activity forecasting model (Jin et al, 2017; Wan, 2016). This makes it possible to test the economic, social and environmental impacts of transport interventions in a systematic way, through accounting for the interactions among transport, land-use and background social-technical trends. Based on this interactive procedure, **Task (2)** makes the assessment of the medium-to-long-term efficacies from alternative transport policy scenarios. In the test of each scenario, the transport model takes the locational predictions to work out the distribution of travel demand and estimate traffic pressures on the transport networks. Whilst the conventional modelling tends to start with incremental and marginal changes in the urban transport system through investment and policy packages (such as the case in well-developed transport networks under small changes in population growth and socioeconomic profiles); our new approach regards longer-term and non-marginal transformations of economy, demography, lifestyles and travel demand, which are undergoing and proceeding in emerging economies.

These tasks have been carried out with a case study in the Greater Beijing Region (consists of the municipalities of Beijing and Tianjin together with the surrounding areas in the province of Hebei). The government's data regulations of restricting overseas studies to using only publicly available data sources have made the case study ideal for testing the new approach. The potential of the new strategic urban transport model has been tested through a wide range of policy scenarios. The results suggest that the new approach in this dissertation has made it not only less expensive and more time efficient to develop a robust model, but could also potentially fill a gap in the lack of medium to long term perspectives regarding major road and metro investments over the next two decades. Such analyses could be of critical importance in improving the performance of the transport system in terms of safety, economic efficiency, air quality, and carbon reduction given the long lead times to plan and implement such transport infrastructure investments.

The rest of this thesis is structured as follows:

- **Chapter 2** reviews the relevant literature regarding two main aspects of **(1)** the existing urban models in terms of their modelling methods and applied forms; and **(2)** GPS-based data and analyses in the scope of transport modelling. Through the literature, we identify the relevant methodologies and applications for further investigation.
- **Chapter 3** develops the methodologies in four domains, which are **(1)** the structure of an appropriate economic and behavioural model; **(2)** a model framework which is capable of representing urban dynamics; **(3)** the development of new model components that can benefit from GPS-related data sources; and **(4)** a practical way to apply the model in response to policy questions through each phase of urban development.
- **Chapter 4** carries out the case study of operationalising the strategic transport model in the Greater Beijing Region based on the methodologies discussed in **Chapter 3**, providing a demonstration of the transport model development with the incorporation of GPS trajectory data.
- **Chapter 5** summarises the short-to-medium-term scenario-test results produced by the case study model as discussed in **Chapter 4**. Model outputs from six widely concerned transport policies have been investigated respectively in comparison against the reference case, casting light on the assessment of different policies regarding road capacity extension.
- **Chapter 6** draws conclusions and proposes topics for future study.

2. Literature Review

2.1. Overview

Economies of agglomeration and proximity can benefit emerging cities and regions with denser population and infrastructure, better connectivity and accessibility, as well as reduced bottom lines for commercial transactions. But without appropriate long-term planning framework, costs can be imposed, constricting the sustainability of economy growth. For instance, cities with long commutes hinder labour force from accessing to available jobs, sapping productivity in Buenos Aires or Ciudad Juarez, Mexico; Traffic congestion and attendant air population impede economic expansion in Bangkok and entail the Thai economy a measurable annum GPS loss; the price of serious air pollution has become increasingly recognised in rapidly growing and industrialising cities with increasing rates of motorisation, such as Beijing and Delhi (UN Habitat, 2016).

To assess the impact of urban planning policies on economy development, the use of model has gained considerable currency with the rise of computing power. Urban models are essentially computer simulations of the way cities function which translate theory into a form that is testable and applicable without doing all the experimentation on the real cities (Batty, 2009). Among all types of urban models, spatial interaction models are the most commonly employed to simulate the connections and interactions between land use and transport systems. Since their inception, the models have gradually grown in sophistication, and their applications have been spreading, adapting to local policy needs and availability of data and modelling skills (Wegener, 2004).

The increasing availability of GPS-based data analyses have triggered new approaches in micro-level analyses of transport networks, as well as personal and vehicular movements. Such new analyses have started to influence strategic modelling (Batty et al, 2013). By incorporating such GPS-related analyses with strategic transport modelling, it can potentially aid transport studies in developing-country cities, which suffer from the scarcity of resources (including appropriate data and skilled professionals) but desire urgent evidence-based support for making major infrastructure investment decisions (such as the development of the entire urban metro networks).

This chapter is intended to serve as a review of urban modelling and GPS-based methods in this context. To form a crucial foundation on which to advance modelling, we deal largely with the techniques that are most relevant to operational urban modelling applications. Some emerging methodologies and applications of analysing the GPS-based data are also discussed.

2.2. Urban models

2.2.1. Existing modelling methods

The existing urban models have sprung from different scientific disciplines and intellectual traditions (Jin et al, 2013). Based on their underpinning modelling methods, these models can be distinguished among five different groups as follows:

- **Production function models**

These models estimate economic activities through a function of production factors. The selection and form of such factors have evolved along with the development of the understanding of what could influence urban growth (Wegener, 2011a).

The classic factors in fiscal policy measures include land, labour and capital (Wegener, 2011a; Aschauer, 1993). Thereafter since the second world war, countries (such as the United States) have experienced accumulation of public non-military capital and relaxation in productivity rate. Hence decisionmakers have implemented a vast scale of urban development programs to stimulate economic growth (Aschauer, 1989). In order to rein the balance sheet, regulators and researchers have conceived public infrastructure (such as percentage increases in streets, highway or mass transit) as a new factor of production (Hulten, 1993). Then the concept of accessibility has been soon introduced to represent not only the scale but also the quality of the transport infrastructures (Keeble et al, 1988). In more recent studies, hybrid approaches have been developed, which have further expanded the accessibility factor to include soft locational indicators (Spiekermann and Neubauer, 2002; Spiekermann and Wegener, 2006; Schürmann et al, 1997).

Production function models stands out in its simplicity. But a main criticism towards these methods is that their econometric estimation lacks the representation of spatial relationships and the contemplation of substitution effects between different production factors (Wegener, 2011a).

- **Spatial interaction models**

Spatial interaction models distribute human activities according to gravitational hypothesis (Batty, 2009). They emphasise the interdependence between land use and transport, and hence can better delineate the locational behaviour of firms and households within a spatial economy (Jin et al, 2013; Jin and Echenique, 2013; Echenique, 2004; Jin and Williams, 2002; Hagen-Zanker and Jin, 2013; Hagen-Zanker and Jin, 2012; Jin et al, 2005).

Born from empirical wisdom, these models have evolved from ad hoc foundations to more reliable theoretical approaches, gaining ground for policy use. Lowry first proposed a computer model for policymaking based on spatial interaction method (Lowry, 1964). This prototype model has enlightened a series of further studies, which fortify the framework with sound econometric and mathematical techniques. For instance, random utility theory has been incorporated to strengthen travel demand forecasting with a solid foundation upon behavioural theory (McFadden, 1974; McFadden, 1973). The integration with input-output analysis has brought a much more detailed statistical picture of the system in the range of manipulation by economic theory (Leontief, 1986; Leontief, 1967). The introduction of floorspace stock model has further adapted the approach into a more comprehensive urban spatial structure (Echenique, 2011; Echenique, 2004; Echenique et al, 1990; Echenique, 1969). Derived from the economic hypothesis that individuals maximise utility, discrete choice model has been applied to analyse the response of users to changes brought by new services, infrastructure investments and transport policies (Ben-Akiva and Bowman, 1998; Ben-Akiva and Lerman, 1985; Bowman and Ben-Akiva, 2001); offering consistent predictions of travellers' choice behaviours (Daly and Zachary, 1978) and prudent insights into the interrelationship between different aspects which influence the individuals' decision making (Domencich and McFadden, 1975). The application of road traffic assignment has made it possible to provide service-level analyses on transport (Sheffi, 1985). More recent studies have been focused on enlarging the scale of models in response to bigger policy challenges, such as climate changes (Batty, 2009). Embedded with GIS platform and big data analysis, these larger models have been built to implement rapid and visually accessible tests pertaining to urban futures (Batty et al, 2013).

These methodological refinements have made the spatial interaction models the most applied and still dominant model in practice (Jin et al, 2013; Batty, 2009). Their popularity has also been courted by the fact that they are parsimonious with data requirements, easier to build and cheaper to operate (Batty, 2009; Lowry, 1964). However, spatial interaction models rarely address endogenous productivity growth and urban dynamics (Jin et al, 2013).

- **Spatial computable general equilibrium models**

Spatial Computable General Equilibrium (SCGE) models are based on microeconomic theory which trades off the demand for space against the cost of transport (Batty, 2009). The equilibrium structure of land values and land uses enables a more comprehensive representation of product diversity and economy of scale (Jin et al, 2013).

The first generation of the models, such as von Thünen model and Alonso model, proposed the idea of using rent gradient or bid rent curve to maximise the yields from rent within the requirement of accessibility (Von Thünen, 1966; Alonso, 1964). Since then, the theoretical framework of SCGE models has been developed over time. Urban issues emerged from 1970s, including the oligopolist or monopolist competition accompanied with new economic geography and the side effects brought by the externalities of urbanisation have nudged economists to combine land use theory with capital and trade theory (Fujita, 1989; Fujita, 1999; Krugman, 1991; Venables, 1996). The path-breaking advance in the theoretical foundation has empowered urban modellers to create polycentric models which allow multiple equilibria in response to the real-world phenomenon that product agglomerates into multiple centres (Anas and Liu, 2007; Anas and Rhee, 2006; Anas and Kim, 1996;). Efforts have also been made to popularise the SCGE models in practice by making plausible assumptions about things which cannot be observed for acceptable costs (Bröcker, 1998a). For policy use, SCGE models have been equipped with the capability to interpret voluntary unemployment using wage curve and to represent activities of the federal government (including collection of taxes and payment of subsidies; Ivanova and Tavasszy, 2007; Oosterhaven et al, 2001). These endeavours have inspired an increasing number of empirical researches about SCGE models (Redding, 2010).

SCGE models can give a fuller representation of product varieties and economies of scale (Jin et al, 2013). But most existing SCGE models are still static, and their dynamic extensions are "recursive" which concatenate stationary equilibria of each period by ad hoc functions (Bröcker and Korzhenevych, 2013; Ivanova et al, 2007a; Ivanova et al, 2007b). This has led to their focus on end state rather than on the trajectories leading to equilibria state (Jin et al, 2013). While a more detailed dynamic form has still been on the longer-term research agenda (Anas, 2013).

- **Aggregate dynamic models**

This group of models is focused on urban dynamics at an aggregate level (Jin et al, 2013). Since Forrester's early attempt (Forrester, 1970), these models have experienced theoretical developments of nonlinear growth and change which generate discontinuities through coupled nonlinearities, threshold effects, or random perturbations (Batty, 2009).

Allen has proposed the idea of "model of complexity", which explores the collective and co-evolving interactions between individual microeconomic actors and the complex system (Allen, 2012; Allen, 1997). Based on the similar idea, Wilson has equipped the nonlinear dynamical framework with a spatial interaction mechanism, allowing the distribution of activities at zone level (Wilson, 2000). With emphasis on the temporal dynamics, Simmonds has built a land use model which can account explicit time lags among different processes of economic actors and the consequent impacts on behavioural changes (Simmonds, 2001). Similarly, Wenger's model has adopted a semi-Markov-based aging sub-model to deal with the dynamic transition rates of different processes (Wegener, 2011a; Wegener, 2001). Zondag and de Jong's model has also included dynamic interactions among sub-models (Zondag and De Jong, 2011).

Aggregate dynamic models better deal with time (Jin et al, 2013). They have been predominantly applied for interpreting the mechanism engines the complex system, enabling researchers to understand and theorise about the processes of changes (Jin et al, 2013; Allen, 2012). However, very few models have been applied empirically (Jin et al, 2013; Batty, 2009). This is mainly because that **(1)** data difficulty has prevented their policy use in practice (Allen, 2012); and **(2)** their disregard for market equilibrium has perplexed insight into how cities evolve (Jin et al, 2013; Simmonds, 2001; Simmonds and Still, 1999).

- **Microlevel models**

In the forms of Cellular Automata (CA), Agent-Based Models (ABMs) or Microsimulation, the last group of models investigates urban dynamics at microlevel (Jin et al, 2013). More specifically, these models represent the actions and behaviour of individual agents located in spaces (Batty, 2009).

Early studies have been focused on indicating individuals and developer decisions, based on empirical researches about the processes of urban growth and development, such as Chapin and Weiss's probabilistic model of urban growth (Chapin and Weiss, 1968) and Ingram, Kain and Grinn's simulation model of housing market (Ingram et al, 1972). Thereafter, the microlevel models have evolved towards a more predictive manifestation. For instance, some models scaled at land-use or activities level, such as UrbanSim and TRANSIMS, can be used to predict urban patterns (Batty, 2007; Waddell, 2002; Smith et al, 1995).

The microlevel models interpret physical inertia explicitly, bringing insights into microscopic interactions between agents (Jin et al, 2013). However, they are not widely applied for policy use. This is mainly due to that many microlevel models largely ignore features of the spatial economy; although some models have been tuned at land use level, their main focus is still at very microlevel where local movements in terms of traffic are being simulated (Batty, 2009)

- **Summary**

This sub section (**2.2.1**) describes the **five** main existing modelling approaches for understanding and predicting urban patterns, including: **(1) Production function models**, which estimate economic activities through a function of productive factors; **(2) Spatial interaction models**, which are built upon the cumulative progress of interactions between land use and transport; **(3) Spatial Computable General Equilibrium (SCGE) models**, which determine choice behaviour based on attractiveness of optional locations at spatial equilibrium; **(4) Aggregate dynamic models**, which address the urban dynamics with nonlinear growth and change of progresses; and **(5) Microlevel models,** which are focused on the microscopic interactions between economic agents.

Through the study of literatures, we have learnt that **(1) Production function models** are simple to implement, but the lack of spatial relationship has hindered detailed trip distribution; **(3) SCGE models** are advantageous with comprehending a wider product variety and representing the impact of economy of scale, but the emphasis on the end equilibria state has led to a overlook on the intermediate trajectories; **(4) Aggregate dynamic models** are better dealing with time, but the data difficulty and disregard for market equilibrium have prevented them from empirical applications; and **(5) Microlevel models** are insightful regarding physical inertia and microscopic interactions, but the neglect of spatial economy and focus on microlevel movement have made them more indicative rather than predictive. For these reasons, these modelling methods cannot be used for building the strategic model for the Greater Beijing Area.

The last option, **(2) Spatial interaction models**, although they rarely address endogenous productivity growth and temporal dynamics, seem likely to be able to fulfil the need of this study for the following reasons: **first**, these models represent detailed spatial relationships; **second**, they consist of specific intermediate states towards the end; **third**, they interpret how cities evolve through progresses of market equilibria; **fourth**, they provide both evaluations and predictions for policy interventions; **fifth**, they moderate data requirement, being comparably easier and less costly to build and operate.

Based on the above literature review, we identify that the modelling approach of **(2) Spatial interaction models** as a potential option for developing the Greater Beijing model.

2.2.2. Applied model packages

Models applied empirically have been built upon different methods as described in the above sub section (**2.2.1**). Through these applications, their methodologies and frameworks can be refined and adjusted to better fit the purposes. Therefore, in this sub section (**2.2.2**), we brief the operational forms of each of the five modelling approaches and discuss their communal features and major differences in policy use.

- **Applied production function models**

Based on the production function approach, models of SASI, ASTRA and MASST reply on a variety of explanatory factors to estimate economic growth (Wegener, 2011a).

SASI is a recursive simulation model of socio-economic development of regions in Europe. It formulates the production function with a comprehensive set of production factors, which represent regional capital, labour market potential, economic structure, sector-specific accessibility, as well as soft locational indicators (Wegener, 2008; Wegener and Bökemann, 1998).

ASTRA is a recursive dynamic model which aims to evaluate the possible impacts of transport policies on the regional economy and environment. It is equipped with macroeconomic components which estimate the inter-industry linkages; its production function includes factors such as natural resources and technical progress; plus its transport sub models consist of both person and good traffic to allow environmental assessment (Dudka, 2007; Fiorello et al, 2010).

MASST (Macroeconomic Sectoral, Social, Territorial) is developed to assess long-term scenarios of spatial development in Europe. It estimates GDP growth and demography based on assumptions of macroeconomic tendencies and policies, and represents the accessibility (as part of the production factors) via a mix of economic potential and distance (Capello, 2007; Capello and Fratesi, 2012).

- **Applied spatial interaction models**

Spatial interaction models have dominated the policy use in practice (Batty, 2009). They predict the location of activities as origins or destinations (or productions or attractions) of trips or commodity flows (Wegener, 2011a). Example models are MEPLAN, TRANUS, PECAS and ITLUP.

MEPLAN is the most operational model and has been applied worldwide. It estimates trade and travel flows based on **(1)** an expanded input-output table with different types of households as consumers of goods and services and as producers of labour; and **(2)** transport costs which are generated through a multimodal traffic assignment module (Echenique, 2004; Rohr and Williams, 1994; Echenique and Williams, 1980; Hunt and Echenique,1993; Hunt and Simmonds, 1993; Hunt, 1994).

TRANUS has gained increasing popularity in Latin American regions. Like MEPLAN, it also simulates the trade flows based on spatial input-output model and transport disutilities (De La Barra, 1989; De La Barra, 1982; De La Barra, 1998; De La Barra et al, 1984).

PECAS (Production, Exchange and Consumption Allocation System) has been applied to an increasing number of North American regions. It further extends the MEPLAN framework to represent "exchange" between the supply and demand of goods and services (Hunt and Abraham, 2005).

ITLUP (embedded in a GIS shell and entitled as **METROPILUS**) has been applied in many urban areas in the United States. Unlike other models of this type, it is not based on input-output coefficients, but a function of access to labour and market (Putman, 1998; Putman, 1991; Putman, 1984; Putman and Chan, 2001).

- **Applied SCGE models**

Applied spatial computable general equilibrium (SCGE) models account for the effects of economies of scale and imperfect competition, such as CGEurope, RAEM and REMI PI+.

CGEurope is the earliest European large scale SCGE model and has been used for transport policy simulations. It considers imperfect competition for inter-regional tradable goods and services, and assumes their prices and quantities are responsive to not only transport costs and times but also incomes and welfare (Brandsma and Kancs, 2015; Bröcker, 1998a; Bröcker, 1998b; Bröcker and Schneider 2002).

RAEM is a bi-regional model applied in Dutch regions. It estimates indirect economic effects of major transport infrastructure investments with incorporations of new economic geography and interregional migration (Oosterhaven et al, 2001; Ivanova et al, 2007a; Ivanova et al, 2007b).

REMI PI+ (Regional Economic Models Incorporated Policy Insight) is the latest version of the original REMI EDFS (Economic-Demographic Forecasting and Simulation) model. Emphasised on the limited supply of land, it has been applied for regional forecasting and policy simulation in the United States (Treyz and Evangelakis, 2018; Treyz et al, 2011; Treyz et al, 1991).

- **Applied aggregate dynamic models**

Applied aggregate dynamic models forgo market equilibrium, assuming that urban system is susceptible to external influences (Jin et al, 2013; Wegener, 2011a; Wegener, 2011b). Example models are DELTA, TIGRIS XL and IRPUD.

DELTA predicts employment through its economic forecasts. It estimates economic activities based on input-output table, and distributes employment through logit models of characteristics of floorspace, such as rent, accessibility and environmental quality (Simmonds, 2010; Simmonds, 2001; Simmonds, 1999).

TIGRIS XL is a recursively dynamic integrated model of land use and transport. It has been used in Dutch national transport policy making and evaluation (Zondag et al, 2015). Its sub model of labour market distributes employment by a function of the log-sum accessibility measures (Zondag and De Jong, 2011).

IRPUD is a land use and transport interaction model. Employment is distributed as a function of availability and attractiveness of floorspace, with consideration of the potential purchasing power for retails (Wegener, 2011b).

- **Applied microlevel models**

Most microlevel models are more indicative rather than predictive (Jin et al, 2013). Hence, very few such models have been used empirically (Batty, 2009). Even though some models, like TRANSIMS (Smith et al, 1995; Nagel and Rickert, 2001), have propelled wide discussions and several case studies; only one example has been found being implemented for policy use: UrbanSim.

UrbanSim is a microsimulation model of locational choice of household and employment. It allocates individual jobs and dwelling developments based on respective sets of indicators of attractiveness, representing microlevel movements of economic activities (Waddell et al, 2003; Waddell, 2002; Waddell, 2000; Waddell, 1998a; Waddell, 1998b; Waddell and Alberti, 1998).

- **Summary**

As discussed, all these models have been applied empirically, bridging the gap between the demand for economic development and the supply of infrastructure investment and labour force. There is no significant difference between their contributions to the great advances in urban modelling (Wegener, 2011a).

Regarding the underlying methodology, these applied models share things in common but also have major differences. They have overlaps, such as the definitional term of spatial impedance and inclusive response to infrastructure policy. For example, they all imitate barriers of accessibility with costs of travel or trade, either in monetary or non-monetary forms; and they all respond to different transport policies with varying results, informing debates for options of major developments. Meanwhile, they also have furcation, which is reflected mainly in four aspects as summarised in **Table 2.1**.

Table 2.1 Comparison of applied urban models

Type	Model	Input-Output	Trade/Travel Flow	Transport Network	Dynamic
Production function	SASI	No	No	Yes	Yes
	ASTRA	No	No	No	Yes
	MASST	No	No	No	Yes
Spatial interaction	MEPLAN	Yes	Yes	Yes	No
	TRANUS	Yes	Yes	Yes	No
	PECAS	Yes	Yes	Yes	No
	ITLUP	No	Yes	Yes	No
SCGE	CGEurope	Yes	Yes	External	No
	RAEM	Yes	Yes	External	Yes
	REMI PI+	Yes	Yes	No	Yes
Aggregate dynamic	DELTA	Yes	Yes	External	Yes
	TIGRIS XL	No	Yes	External	Yes
	IRPUD	No	Yes	Yes	Yes
Microlevel	UrbanSim	No	Yes	External	Yes

Source: <Wegener, 2011a>

The **first** difference among these models is whether they adopt **input-output** table to determine locational choices. Spatial interaction models (except ITLUP), SCGE models and a few aggregate dynamic models (i.e. DELTA) estimate the locations of economic activities based on input-output coefficients. Instead, the other models use logit-based functions of locational choice factors.

Their **second** disparate aspect lies in the representation of **trade and travel flow**. Production function models aggregate the flows as part of the accessibility factors. But all other models simulate zone-to-zone trade and travel flows in an explicit manner, enabling detailed spatial analyses and service-level insights.

The **third** difference is whether the **transport network** is incorporated within the model. All the spatial interaction models, as well as a few production function model (i.e. SAS) and aggregate dynamic model (i.e. IRPUD), integrate the transport and land use modules tightly to establish the interactive mechanism between transport costs and location distributions. Other models are either depending on the results of external transport models or exogenous transport inputs without any network.

The **fourth** divergence comes from their different ways of specifying temporal **dynamics**. Production function models represent dynamics in a recursive manner with user-supplied time lags between submodules. All spatial interaction models calculate market equilibria at the end of each period. One SCGE model, CGEurope, converges to equilibria only at the start and end states. Other SCGE models (i.e. RAEM and REMI PI+), aggregate dynamic models and microlevel model (UrbanSim), allow varying time lags between different progresses of economic activities and between changes of behaviours.

These observations confirm our findings from the study of their underpinning methodologies that spatial interaction models better fit to the purpose of this thesis, for the reasons summarised in Section **2.2.1**. In addition, their applied model packages stand out in terms of that **(1)** they yield explicit spatial analyses and service-level evaluations; and **(2)** they synergise the essence of land use and transport through close and interactive integration of both.

2.3. GPS-based microscopic data and analysis

2.3.1. Existing applications

The Global Positioning System (GPS) technology has established its reputation as the most popular global positioning method since its emergence in 1960s (Kaplan and Hegarty, 2005). It has been embedded into various kinds of portable electronic devices, such as smart phones, tablets, and vehicle-mounted devices. Data collected from such GPS-equipped devices has been widely applied in many scientific fields; and regarding the era of strategic transport modelling, its applications are mainly focused on four difference aspects as follows:

- **Construction of road networks**

Researchers have introduced the GPS trajectory data into the creation of digital maps of road networks. Compared with the conventional map generation approach (such as survey and satellite image), GPS technology advances in its ubiquity and promptness; hence is potentially capable to bring up-to-date road network information in a more efficient way (Mintsis et al, 2004; Shi et al, 2009).

Cao and Krumm proposed a promising approach to automatically convert raw GPS traces from everyday vehicles (from GPS loggers installed on 55 Microsoft Shuttles) into a routable road network in the Microsoft campus in Redmond, Washington, USA (Cao and Krumm, 2009). With the availability of massive GPS traces, researchers can testify their approaches in a wider stretch of study areas. For example, Shi et al abstracted road network in Jilin City in China using massive GPS trajectory data which were collected by in-vehicle GPS loggers (Shi et al, 2009; Shi and Liu, 2010); and Zhang et al inferred Beijing City road network with 5.75 million GPS traces from 200 taxis (Zhang et al, 2017).

Across through these studies, the detection of road intersections remains as a challenging component in the construction of road networks. OpenStreetMap project applied an approach which allows its volunteers and registered users to manually edit and improve the transport network information which was derived from the hand-held GPS devices (Haklay and Weber, 2008). Aiming to improve the efficiency, Alireza and Krumm demonstrated an unsupervised pattern recognition method for identifying road intersections automatically using detailed GPS traces of everyday vehicles (Alireza and Krumm, 2010).

In the literature of this problem, we can see that different methods have been developed, but all require the input of quality and massive GPS trajectories with detailed information (such as position, speed and direction) and consistent sampling rate (for example, one sample per 10 seconds). Furthermore, the application in practice requires considerable manual inputs to edit and validate the network information, which can be very costly and time-consuming (Alireza and Krumm, 2010).

- **Estimation of vehicular speeds or travel times**

The requirement for detailed and accurate travel time, vehicle speed and delay data are important for the calibration and validation of model system (de Dios Ortuzar and Willumsen, 2011). Conventionally, this average link speeds or travel times can be collected by one or a few probe vehicles, which record the relevant information while moving at the average speed of traffic stream along the survey road links for a specific time period. But this 'moving observer' method can be costly and subjective to the driver's perception of 'average speed'.

With the availability of GPS trajectory data, practitioners have been seeking for a more efficient and objective way to reach the data. One successful example would be the TrafficMaster travel time data, which is obtained from in-fleet GPS devices and has been provided to transport modellers in the UK since 2012 (Highways England, 2018). However, the coverage of the data limits to strategic roads and 'A' roads, where GPS signals are more stable, and the topology of road links are simpler (Department for Transport, 2015).

In dense urban areas, where signal glitches are fitful and road networks are complex, the GPS trajectories are more likely to be sparse with low sampling rate and dented by faulty displacement. It is thus difficult to use the data to derive vehicular speeds or travel times. Recent studies have arisen towards investigating advanced map-matching algorithms, which facilitates the estimation of travel times by allocating sparse GPS trajectory data onto urban or suburban road networks. Targeting low-frequency GPS data (e.g. one sample per 2 minutes), Yuan et al develop a supervised map-matching algorithm which positions a GPS point on the road map in consideration of the tendency of its neighbouring data points (Yuan et al, 2010a; Yuan et al, 2010b). Focusing on poor-quality GPS data collected by mobile phones, Bierlaire et al propose a probabilistic map-matching approach, which generates a set of potential paths, and calculates a likelihood with each of them using both spatial and temporal information of the raw GPS data (Bierlaire et al, 2013). More recently, Quddus and Washington develop a shortest-path based map-matching approach, which were gauged against a high-accuracy integrated navigation system; and the results suggest that the algorithm has an impressively high accuracy of 98.9% when running with the 30-second-sampling-interval GPS data (Quddus and Washington, 2015).

The average link speed or travel time data can thus be achieved based on the appropriately map-matched GPS trajectory data. Tao et al demonstrated an example of using mobile phone GPS data to estimate average link speeds; their source data is relatively a good quality with frequent sampling rates (1 sample per 10 seconds), and hence the method allows an inconspicuous map-matching progress for the price of a strict data filtering and screening process (Tao et al, 2012).

The studies of this problem have opened a new door to the estimation of link speed and travel time data using sparse and coarse GPS trajectory data. The collection of such low-quality GPS data is relatively more facile, allowing the estimation of palatable link speeds or travel times with a greater spatial coverage and a tighter budget. For this reason, we believe that this application worth further investigation and its detailed literature will be discussed in **Section 2.3.2**.

- **Detection of activities or trip ends**

Research community has considered to use GPS trajectory data to conduct travel survey, which is the primary source information for understanding and modelling dynamics of travel behaviours (Marra et al, 2018; Servizi et al, 2019). This requires dividing the GPS trajectories into activities and trips (we will discuss the identification of trips in the next following bullet point).

Central to the problem is to automatically spot when a user or driver standing in a place for a long time period. Earlier studies flag an activity when it meets a combination of criteria. For example, Stopher et al infer a trip end in consideration of differences in several aspects of a sequence of GPS points, including distance (less than 15 metres or 0.000051 degree), course heading (equal to zero or unchanged), speed (equal to zero), and dwell time (no less than 2 minutes) (Stopher et al, 2005). More recently, density-of-point based approach has been widely applied, which detects an activity where the density of the successive points along a GPS trajectory in a certain area is greater than a specific threshold. Schuessler and Axhausen's study represents a "bundle of GPS points" method, which finds out an activity when more than 2/3 of a number (at least 30) of the preceding and succeeding GPS points are positioned within a 15 metres radius around the GPS point in question (Schuessler and Axhausen, 2009). Due to the low precision of GPS data, Marra et al's study applies a greater search radius and sets the criterion as that at least 2 successive points for at least 15 minutes in a radius of 250 metres (Marra et al, 2018).

Although the approaches of the above studies are born of experiences, their main task accord with the mission of the pattern-recognition analysis, which recognises the regularity or pattern from a bunch of data (for example, finding trip ends in GPS trajectories). Besides, with the allowance for low-quality GPS data input, the idea behind can be promoted forwards to wider applications, such as identification of road intersections and congestion hotspots. With these inspirations kindled by the literature of this problem, we will explore the studies of using pattern recognition algorithms to detect hotspots of sluggish GPS traces in **Section 2.3.3**. This further exploration also complies with the need in this thesis of sense checking the source GPS data, by comparing the identified locations of congestions against our local knowledges.

- **Definition of trips**

By definition, a trip is the connection between two consequent activities, representing a movement from one place to another (Marra et al, 2018). But this does not imply that it is effortless to define a trip when activities are all presented, because the task involves haunting undertakings, such as segmentation of trip stages and detection of travelling modes. Each of these sub tasks has invoked a stream of studies.

Almost all the approaches developed to identify different trip stages rely on the variance of travelling speeds. They can be bifurcated as follows. First, some studies apply capping velocities and accelerations to identify on-foot trip legs from the in-vehicles, see examples in the studies of Zheng et al (Zheng et al, 2010) and Gong et al (Gong et al, 2012). Second, some other studies segment trips by spotting the brief stops in the transition between two different trip legs. For instance, Zhang et al identify a stop when the speeds of at least 5 consecutive data points are below 0.5 metre per second (Zhang et al, 2011); and Biljecki et al consider non-moving data points (speeds equal to zeros or very small) as stationaries between trip legs (Biljecki et al, 2013).

For the second sub-task of mode detection, researchers have developed various classification methods, which can automatically and effectively classify trip legs into different modes. Zheng et al establish a probabilistic classifier using ground-truth training data samples, which can calculate the probability of using a specific mode along a trip leg (Zheng et al, 2010). Reddy et al’s classification system relies on a stochastic decision tree, which can accurately identify different active modes, such as walking, running and biking (Reddy et al, 2010). Stenneth et al's research emphasises the identification of public transport modes (such as bus and over-ground rail) using stochastic models (Stenneth et al, 2011). Montoya et al's research applies strict filtering process to infer multiple travel modes (Montoya et al, 2015). In more recent studies, machine learning techniques have gain popularity, and Koushik et al provides a detailed review of relevant studies (Koushik et al, 2020). An example can be found in Dabiri and Heaslip's study, which builds the travel-mode classifier based on neutral network (Dabiri and Heaslip, 2018).

Through the literature of this application, we can see that the identified multi-mode trips can be potentially helpful in various stages of strategic transport modelling, such as the base demand matrix building and the modal-share calibrating. However, there are two existing limitations regarding its requirement of high-quality data input: First, to make the resulting trips representative for the whole population, the size of the sample GPS trajectories should be adequate and comprehensive. Second, almost all recent approaches establish their classifiers using reliable "ground-truth" training data, which can be costly to obtain and difficult to judge. Furthermore, the accuracy of trip definition may need further verification and validation, even with well-establish commercial providers (such as Google Maps and Apple Maps). A digressed anecdote is not cushioning the blow from our suspicion: a German man successfully outsmarted the Google Maps algorithm by carting round 99 phones, tricking it into thinking there was a traffic jam in Berlin (Unilad, 2020).

- **Summary**

This sub section (**2.3.1**) casts light on the literature of applying GPS trajectory data in strategic transport modelling. We have reviewed four applications, including **(1)** construction of road networks, **(2)** estimation of vehicular speeds or travel times, **(3)** detection of activities or trip ends, and last **(4)** definition of trips.

Both the first and the last applications (the construction of road networks, and definition of trips) require massive and quality inputs of GPS trajectory data, as well as further demanding works of output verification and validation. This has thwarted our further exploration in these two aspects.

The input requirement for the second and the third applications (estimation of vehicular speeds or travel times, and detection of activities or trip ends) is relatively unconstrained, allowing low-quality and sparse GPS trajectories. In addition, the outcomes are comparatively easier to testify and validate, and can play an important role in strategic transport modelling.

Therefore, also in consideration of the data availability in the study area, we identify two topics for further investigation, as follows: **(1)** to estimate congestion link speeds using GPS trajectories, which results can be potentially used as part of the disutility function in modelling route choice; this requires the data source capable of representing the level of congestion in the real world in the case study area; and hence, **(2)** we will also study the pattern recognition techniques, which can help identifying hotpots of non-moving or slow-moving GPS data points, which results can be compared against our local knowledges and guides in order to sense check the originality and quality of the data source. Detailed literature around these two topics is discussed respectively in the following two sections.

2.3.2. Map-matching method for estimating congested link speeds using GPS data

The data of road link speeds in congested conditions is an important input of the strategic transport model, playing a crucial role in the traffic assignment module for route choice modelling. The data is used to be sourced from survey data or empirical estimation, which is either costly or questionable. Especially in emerging regions, the fast pace in the development of infrastructure has brought greater difficulty with probing such data. As discussed in the above section, by introducing GPS-based analysis, a direct estimation of time-sliced congested link speeds can become approachable.

Such GPS-based analysis should be facilitated with a robust map-matching method, which translates the continuous-space positioning information into network-based topological representation (Deng et al, 2015). More specifically, the method typically integrates GPS data with road networks, identifying the correct routeing and inferring the correspondence between trajectory points and road links (Greenfeld, 2002; Quddus et al, 2007; Ochieng et al, 2003). The accuracy of the map-matching method depends on the granularity of the digital road network as well as the quality of the GPS data (Deng et al, 2015; Yuan et al, 2011a; Yuan et al, 2011b). While its effectiveness is mainly decided by the underpinning algorithm (Parkinson et al, 1996; Chen et al, 2005). These are particularly relevant when input data is sparse with low sampling rate and where the application is massive in scale: as in the case of this thesis which aims to build a macroscopic model for the Greater Beijing Region, where GPS loggers can lose signal in the dense urban areas, and their frequencies are set below 0.01Hz to reduce power consumption.

There are a wide range of map-matching methods, which aim to deal with low-frequency GPS data (Wang et al, 2011; Miwa et al, 2012; Ye et al, 2012; Hunter et al, 2013; Chen et al, 2014). An early attempt has been made by Lou et al (2009), which develop the ST-matching approach to construct a routable road map using GPS data with low sampling rate based on a scoring system. Another work from Rahmani and Koutsopoulos (2013) demonstrates a robust map-matching method which incorporates observed data to effectively infer paths for sparsely distributed GPS traces with limited information (only with location and timestamp). Zhu et al (2013) propose a map-matching method which particularly aims to calculate the link travel times based on the maximum likelihood between estimates and observations; their study uses taxi GPS data from New York, and has been applied in the urban area of Manhattan.

These studies have casted a new light upon how we can utilise sparse GPS data to estimate congested road link speed in busy urban areas. They have demonstrated effective map-matching algorithms for GPS trajectories with low sampling rates, based on reliable observed data and gridded road networks (such as Manhattan). However, these benefits are absent in Beijing, where lacks publicly available observed data but has a much more complex urban road network. This means that **(1)** sense check should be carried out to ensure the source GPS data is representative for the level of congestions at different places in the Beijing road network; **(2)** a new map-matching approach and consequently a new method of calculating the congested link speeds are required. The methodologies underpinning these tasks are further discussed in **Chapter 3**; in the next following subsection, we represent a literature review about recognising patterns for slow-moving and non-moving GPS data points, for the purpose of data checks.

2.3.3. Hotspots recognition of slow-moving and non-moving GPS points

As discussed in **Section 2.3.1**, another branch of GPS-based analysis is related to identifying the patterns of traffic, particularly slow-moving and non-moving traffic. Such congestion patterns, when compared with our local guides, can potentially provide insights into whether the raw GPS sample data can reflect the real-world level of congestions. Therefore, the possibility of using them to identify congestion hot spots are pursued further here.

Pattern recognition is in general terms a branch of data mining that focuses on the recognition of patterns and regularities in data (Bishop, 2006). One well-studied example is cluster analysis or clustering, which is originated in 1930s (Driver and Kroeber, 1932; introduced to psychology by Zubin in 1938 and Robert Tryon in 1939; Zubin, 1938; Tryon, 1939); and famously used by Cattell beginning in 1943 for trait theory classification in personality psychology (Cattell, 1943). Cluster analysis attempts to assign each input values into one of a recognized or given set of classes, based on their variations in similarity or distance to each class. More precisely, it is a general task to be solved of grouping a set of inputs in the way that objects in one same cluster (or group) are more similar or closer to each other than to the other inputs which are in other clusters (groups) (Bailey, 1994). Indeed, clustering analysis can be formulated as a multi-objective optimization problem, rather than one specific algorithm. This is firstly because the appropriate clustering algorithm and the corresponding parameter settings (such as distance or density threshold, or minimum number of expected records in each cluster etc.) depend on the nature of input dataset and the purpose of using the results. Moreover, it is often a supervised but not an automated task, which involves iterative process of both knowledge exploration and parameter configuration. Nowadays, this topic has been studied in many diverse fields, including machine learning, computer science, psychology, cognitive science, ethology, and transport studies etc.

Keeping in mind that clustering or cluster analysis is not one specific algorithm but an optimization task, it is reasonable to consider a 'cluster' as a group of data objects with most similar properties according to some algorithm. Clusters identified by different clustering models or algorithms can vary significantly from each other. Typical models and their underlying algorithms can be categorized into five types:

- **Connectivity models**

Also known as hierarchical cluster analysis (HCA), it is a clustering method which tries to build the hierarchy of clusters. Popular algorithms based on this model are known as single-linkage clustering, such as the minimum of object distances (Everitt et al, 2011); complete linkage clustering, such as the maximum of object distances; Sibson, 1973); or average linkage clustering (UPGMA – Unweighted Pair Group Method with Arithmetic Mean; Defays, 1977). Those algorithms produce a hierarchy structure rather than a series of trimmed datasets. Such kinds of algorithms have obvious limitations in efficiency and accuracy when processing large-scale dataset with substantial randomness, such as urban-scale taxi GPS trajectories.

- **Centroid-based models**

This clustering model partitions input objects into clusters with approximately similar number of objects, and represents each cluster by the centroid point. Typical algorithms of this model are named as ‘k-means’, which assigns objects to the nearest cluster centre by shortest mean value of distance (Lloyd, 1982). Most k-means-type approaches need to specify the number of clusters (k value) in advance; but for large-scale data with substantial uncertainties, this value is often impossible to determine beforehand. Moreover, the preference of approximately similar-size clusters, can often lead to incorrectly trimmed borders between clusters (Hartigan, 1975; MacKay, 2003; Hartigan and Wong, 1979).

- **Distribution-based models**

This model identifies each cluster with objects which are most likely to have the same distributions. The expectation maximization (EM) algorithm is often used in such models. The well-structured theoretical foundation of such approaches allows them to easily resemble the ways in which artificial data is generated, by identifying random data records from their distribution. But they often suffer from the overfitting problem when there are too many possible probability distributions (Xu et al, 1998). In practice, naturally occurring data has few precisely defined mathematical distributions. These approaches may therefore be unsuitable for practical uses.

- **Density-based models**

These models classify clusters as areas through detecting density differences, e.g. a cluster can be identified through having higher density than the remaining data objects. Objects in other sparse areas are considered as noise or border points. The most widely used density-based algorithm is the Density-based Spatial Clustering of Applications with Noise (DBSCAN) (Ester et al, 1996; Ankerst et al, 1999; Achtert et al, 2006; Kriegel et al, 2011; Kailing et al, 2004). DBSCAN introduces the concept of ‘density-reachability’, which is used to determine whether some points are connected to one another in the form of a cluster in terms of areal density. If a set of objects reach a certain level of high density to each other either directly or indirectly, then such a set can be defined as a cluster if there are enough points inside the cluster. The main criticisms towards DBSCAN are that the method expects a density drop in order to detect cluster borders, and it is not capable of detecting intrinsic cluster structures (Roy and Bhattacharyya, 2005).

However, the method has obvious advantages when used to process large-scale geographical dataset with uncertainty and randomness. First, DBSCAN allows clusters in arbitrary shapes; this feature offers an opportunity to explore the geometry dynamics of the GPS trajectories on sophisticated urban road networks. Second, the approach is comparatively easy to operate with few complications, as it discovers the same results in each run and has no need to run the procedure for multiple times. This can obviously enhance the efficiency of data processing in cases of large-scale or mega-scale datasets (usually over million records).

- **Other models**

There are still other kinds of models besides the four above, such as the subspace model, group model, and graph-based model (Can and Ozkarahan, 1990; Ng and Han, 1994; Huang, 1998; Agrawal et al, 2005; Sculley, 2010). Under the structure of each model, various algorithms have been developed to tackle different problems with clustering identification. Meanwhile, considerable and increasing efforts have been made to improve the performance of existing algorithms, due to the rising willingness of and demand for processing smart data sources (Huang, 1998; Sculley, 2010).

- **Summary**

In view of the benefits of DBSCAN approach, it would be considered as the most suitable method in this study for identifying hotspots for parking, stopping and congestion using taxi GPS traces. We will return to this discussion with, and there has a specification of the methodology in **Chapter 3**.

2.4. Summary

The literature review in this chapter falls into two themes. The first theme investigates the urban models in terms of their underlying approaches and applied packages. The second theme briefs studies about the GPS-based data and analyses which can be potentially applied in the development of strategic models.

In the first theme, over the studies of urban modelling methods, we have learnt that urban models can be categorised into five different groups as follows:

(1) Production function models;
(2) Spatial interaction models;
(3) Spatial computable general equilibrium models;
(4) Aggregate dynamic models; and
(5) Microlevel models.

The first group **(1) Production function models** estimate economic activities using different forms of functions of locational factors. Being focused on the aggregate effect of trade and travel flows, the applied forms of production function models, in most of the cases, depend on external transport model or exogenous transport inputs. The most operational group **(2) Spatial interaction models** emphasise the interactive feedbacks between land use and transport. Almost all their applied models are integrated with comprehensive transport networks, providing detailed spatial and service-level analyses. The microeconomic-based group **(3) Spatial computable general equilibrium (SCGE) models** compute multiple equilibria in response to the real-world phenomenon of imperfect competition and economic agglomeration. Operational SCGE models represent wider product varieties and economy of scale. But most of the SCGE models also depend on external transport inputs, and their treatment of temporal dynamics leads to an overlook at the intermediate states. The next group **(4) Aggregate dynamic models** underscore the temporal discontinuities induced by nonlinear growth and external influence. Applied models of this type allow dynamic time windows for different economic progresses and behavioural changes. But they omit market equilibria, and mainly rely external transport models on calculating accessibilities. The last group **(5) Microlevel models** embody the spatial relationship between individual agents. They insight into the microlevel interactions but often ignore the wider spatial economy, becoming more indicative rather than predictive. Very few such model has been applied in policy use, although discussions have been invoked about broadening their further applications.

As this thesis aims to build a strategic transport model for policy use in developing regions with data and cost constraints, the second type of **(2) Spatial interaction models** seem like best fit for our purpose. Unlike **(1) Production function models**, which aggregate flows into one complex variable of accessibilities, spatial interaction models specify economic activities explicitly in the space, enabling detailed spatial analyses. Different from **(3) SCGE models**, which emphasise market equilibria at the start and end states, spatial interaction models phase along the trajectory towards equilibrium, inferring how cities evolve. Compared with **(4) Aggregate dynamic models**, which respond to temporal incoherence, spatial interaction models embrace more relaxed data requirement, easing difficulty in model development (more or less). In contrast to **(5) Microlevel models**, which apprehend actions and behaviour of individual agents, spatial interaction models undergo wider empirical applications, gaining ground in policy use. In addition, spatial interaction models integrate land use and transport into their interactive mechanism, enabling service-level analyses of transport policies at a fine spatial granularity.

Through the first theme about urban models, we identify spatial interaction models as a potential approach to developing the strategic transport model in the Greater Beijing Area. In the second theme of this chapter, we discuss the GPS-based methodologies and applications in urban transport modelling, in the search of a possible way to wind down the data-related and budgetary constraints in the local area. Therefore, we have discovered four main applications which could potentially benefit the model building, including:

(1) Construction of road networks;
(2) Estimation of vehicular speeds or travel times;
(3) Detection of activities or trip ends; and,
(4) Definition of trips.

The first application of **(1) Construction of road networks**, aims to develop more efficient methods of creating up-to-date digital maps of road networks using GPS trajectories. But to establish accurate and detailed networks, it requires not only quality and ample GPS trace data as input, but also intensive endeavours to reassure the output. Recent studies in the second area **(2) Estimation of vehicular speeds or travel times** enlighten a new path of estimating link speeds and travel times using low-quality GPS traces. Studies have been arisen to use sparsely distributed and low-quality GPS traces to derive link speed and travel time results. The third group of studies **(3) Detection of activities or trip ends** specify activities at trip origins and destinations by investigating regularities or patterns from a bunch of GPS data points. Among their applications in establishing travel surveys, quality and massive GPS data is essentially required to achieve detailed and representative outcomes. But the idea behind can be put forward toward wider and more general applications upon the usage of sparse and low-quality input data, such as identification of hotspots for non-moving or slow-moving vehicles. At last, the research about **(4) Definition of trips** explore new ways to identify trips between pairs of activities, defining their characteristics (such as trip stages and user modes) using GPS trajectories. The study also requires a massive amount of quality and informative GPS trace data. But even the well-established merchants, given adequate input data and contemplated algorithms, still hand out resulting trips with obvious uncertainties.

The lack of appropriate data in Beijing has hindered us from investigating **(1)** and **(4)**, which both rely on massive amount of quality and informative GPS trajectory data. In contrast, the input requirement for **(2)** and **(3)** is less constrained, allowing further exploration and implementation with more reachable data. In applications of **(2) Estimation of vehicular speeds or travel times**, sparse and low-quality GPS traces can be put through delicate map-match algorithms to derive link speeds and travel times, providing a much more affordable way to obtain the data in comparison with the conventional 'moving-observer' approach. The ideas behind **(3) Detection of activities or trip ends** inspire us with using sparse GPS data to identify hotspots of slow-moving and non-moving vehicles, which results can be used to check the consistency between the source data and the local knowledge. This means that in our study, **(3)** will need to be carried out first for the purpose of data sense-checking, and then **(2)** will follow to derive the road link speeds under congested conditions which would otherwise by very costly to assemble.

Building on the new thinking of using GPS data, we discuss the modelling methodology in **Chapter 3**.

3. Methodology

3.1. Overview

The literature review in **Chapter 2** indicates that spatial interactive models are commonly recognised as one of the most effective tools to support the policy makers and planners through predicting the direct and indirect effects caused by alternative policy interventions, in both long-term and short-term standpoints. Advances in economic and econometric theories continue to offer new insights into the modelling of interdependent activities between land use and transport. There can be different formulations of the strategic transport model depending on the core policy questions, data availability, and modelling capabilities available.

In this chapter, we explore the methodology for establishing a model with spatial interaction approach at heart, which could be applied to measure the complex impacts of different policy interventions and be digest easily by the policy makers and urban planners.

This would demand four levels of model building as follows: **firstly**, a flexible and effective modelling framework which represents the main economic interactions of the urban region over time; **secondly**, a careful grounding of the main concepts in robust modelling approaches; **thirdly**, a continuous development of new model components that can benefit from emerging data sources; **fourthly**, an approach to adapt this general model structure to suit the policy questions of each phase of urban development, in a way that is empirically sound and easy to present to the decision makers and the public. We discuss these four aspects of the methodology in this chapter.

3.2. Modelling framework

3.2.1. Whole model structure

The whole model, with an explicit spatial interaction model at the heart, plays a central role especially in **(1)** providing spatially differentiated production and consumption costs among all locations in the study area for business, household and investment activities, so that the production functions and location choices can directly reflect the specific transport costs and travel choices; **(2)** estimating spatially differentiated demand for travel which are sensitive to both transport supply and the land use patterns of production and consumption; **(3)** establishing the foundation for spatial equilibrium of urban activities, which are of critical importance for medium to long term planning.

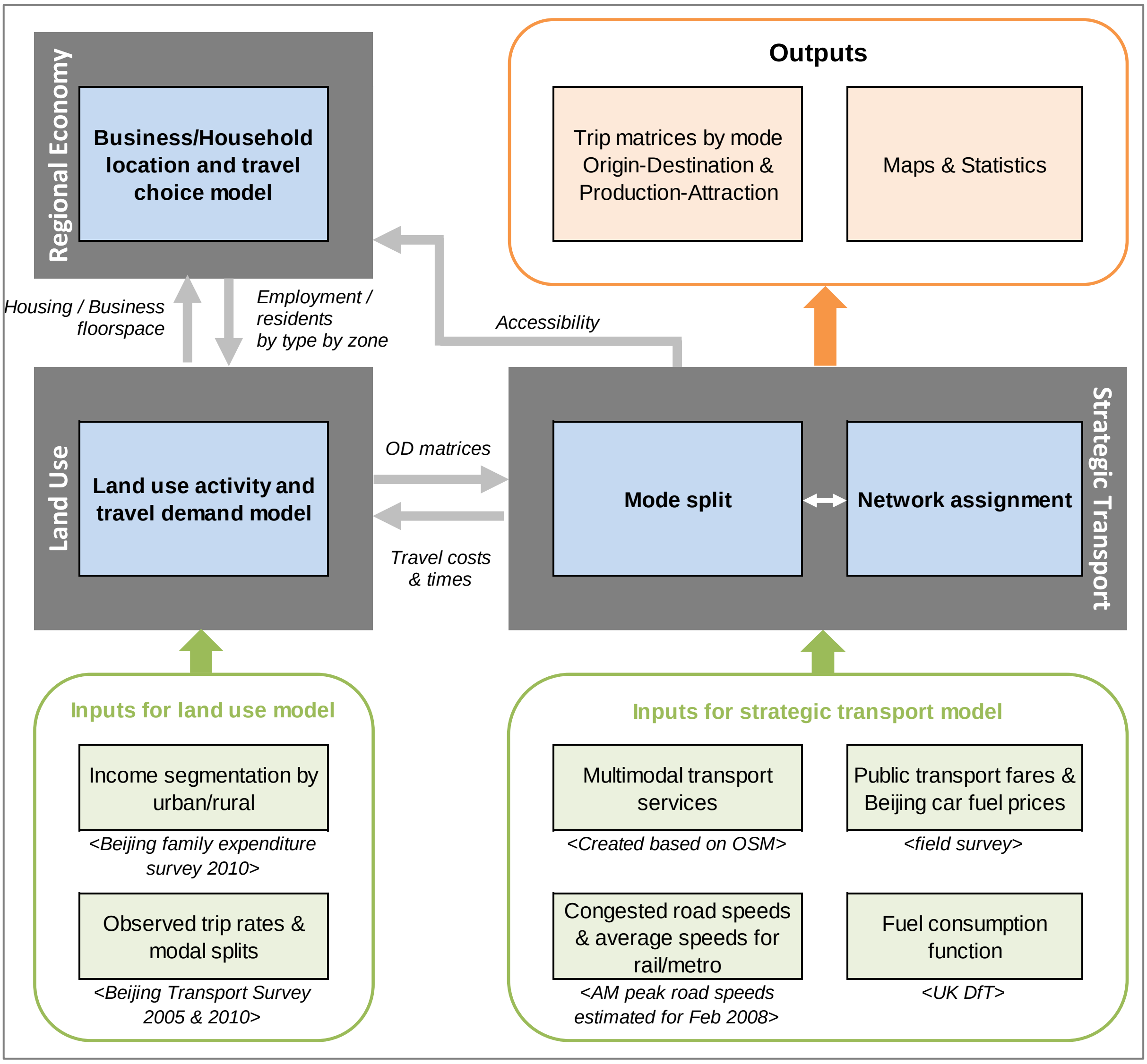


Figure 3.1. Whole model structure
Reference: <Jin et al, 2017>

The structure of the whole model is illustrated in **Figure 3.1**. As seen, the model consist of three fundamental components (see dark grey boxes in **Figure 3.1**), including: **(1) Regional economy model** estimates location and travel choices for millions of businesses and households based on a recursive spatial equilibrium (RSE) approach (Jin et al, 2013; Wan, 2016); **(2) Land use model** allocates land and building investments and ad hoc policy interventions with dynamic churn rates, nonlinear growths, and also forecasts travel demand (Xiao, 2016); **(3) Strategic transport model** follows executes modal split and network assignment, distributing the Origin-Destination trip matrices onto the transport networks, and generating the outputs. Both conventional and novel, crowdsourced data have been used to establish, calibrate and validate the modules (Jin et al, 2017).

These modules interact with each other. For instance, the regional economy model and land use model determines the transport demand for the strategic transport system, and in return, the strategic transport system adjusts the zone-to-zone accessibility for the regional economy model which then make an impact on the land use model (Jin et al, 2017; Williams, 1994). There is also feedback mechanism between different submodules within each of the components. For example, within the strategic transport model, modal split and network assignment are interacted to each other to achieve equilibrium.

Although in this dissertation our focus is the strategic transport module, we fully recognise the fact that the design of the strategic transport module cannot be isolated from the other modules. Accordingly, we discuss below the strategic transport module as an integral part of an integrated model system, which endows the strategic transport model to interact with the land use model (Rong, 2016) and the RSE economic model (Jin et al, 2013; Wan, 2016).

3.2.2. Integrated LUT model

We predict the medium-to-long-term interactions between land use and transport (LUT) by integrating the land use and strategic transport modules. Based on the established models such as Jin et al (Jin et al, 2002), the integrated LUT model has been designed with a series of steps to allow not only tests of the impacts of specific policy and system design interventions, but also insights into major strategic alternatives in land use and transport layouts; providing evaluation and analysis regarding the appropriate levels of current investments and future options for infrastructure expansion and intensification.

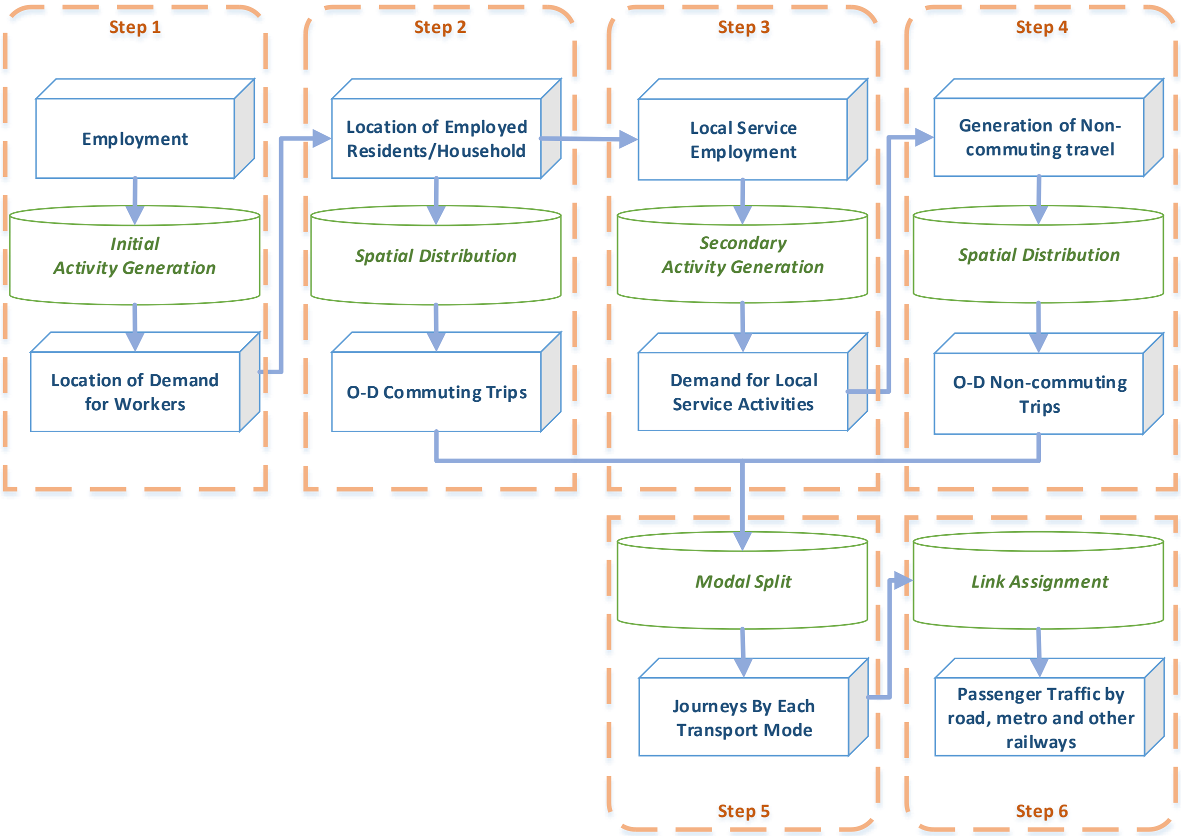


Figure 3.2. Main steps of integrated LUT model

As shown in **Figure 3.2**, these main steps are:

(1) **Employment location.** Employment demand in the model is generated from the demand for goods and services, the production of which is in turn determined by the production functions. For the medium to long term, most of the employment is assumed to be responsive to the supply of labour, business floorspace as well as the demand for production, as specified in the production functions. The coefficients of the production functions are calibrated in the Calibration Year and can be modified for each time period as land use and transport conditions change, or indeed for each major policy scenario.

(2) **Residential location for households that contain employed people and those that contain no employed people.** The demand for labour as generated by the production functions above is then distributed to all residential zones through the modelled probabilistic choice of residential location via a logit-based discrete choice model. The resulting flow of employed residents from residential zones to work zones becomes the underlying pattern for journeys to work. The probabilistic choice is influenced by the cost of living and a monetised non-pecuniary attractiveness at each residential and employment zone, and a generalised commuting cost between the residential zone and work zone. The location of non-employed households (i.e. households that contain no employed people) are modelled

separately, assuming that they move between residential zones in a way that is dictated by the lifecycles of those households

(3) **Secondary activity generation.** Both employed and non-employed households are to generate the demand for housing, consumer goods and services, and non-commuting travel such as journeys to school education, to services and for business purposes. This demand is fed into (1) above. The secondary activity generation is based on step (1) and (2), and completes all activities and trip production in the model.

(4) **Spatial distribution for non-commuting trips.** The non-commuting trips are segmented by purpose, such as school education, business travel and other personal travel. They are attracted to either service employment or the households as appropriate. Logit-based discrete choice models are applied to distribute the trips between each pair of production and consumption zones.

(5) **Model Split.** The commuting and non-commuting journeys are attributed to modes of transport that are available between each pair of origin and destination zones, according to the modal choice behaviour of each socio-economic group, for each travel purpose.

(6) **Link Assignment.** The journeys on each mode are then assigned to the morning peak road and rail (including metro) networks using a stochastic user equilibrium algorithm, which can either incorporate road and rail service capacity restraints, or assigned free of capacity restraints to explore future network capacity demands under alternative planning scenarios. In the Calibration Year, observed congested speeds on road links will be required in order to calibrate the model in an effective way.

In the above, Steps **(1)** - **(4)** are regarded as the land use component, which replaces the trip generation and trip distribution steps of a conventional four-step model. These steps are a separate research stream (Jin et al, 2017; Rong, 2016). Steps **(5)** and **(6)** are the main contents of the strategic transport module.

3.2.3. Run through time

For medium to long term policy and operational intervention assessment, it is necessary to run the model through time (typically for a few decades). The linking of the land use and transport modules via an interface module is shown in **Figure 3.3**. First of all, the Calibration Year land use and transport model is a starting point for the sequence of predictive model runs. This subsequently includes a Validation Year model run in predictive mode so that the model predictions can be assessed through comparing the model predictions with the observed activity patterns for that year.

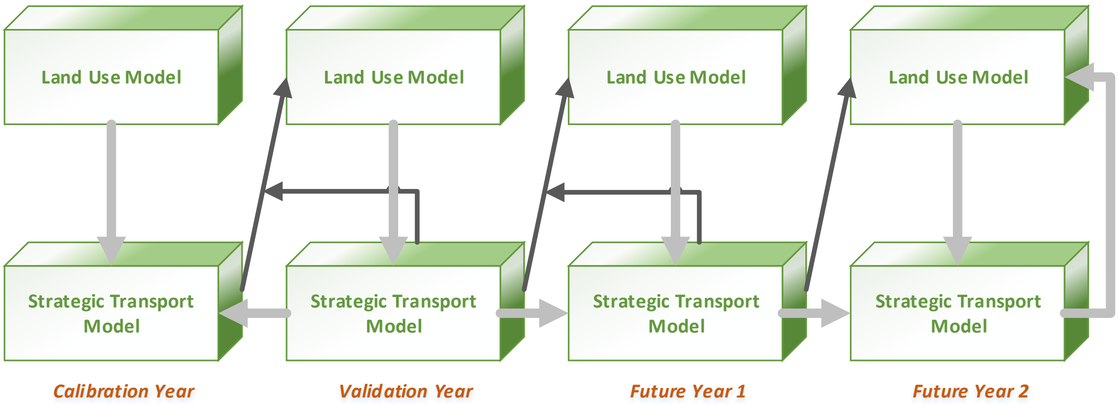


Figure 3.3. Run integrated LUT through time

Typically, it is easier to collect very recent transport network and services data than, for example, five or ten years ago. This implies that when a new transport model is being built for a city region, the network and services data for the validation year may be more complete than for the calibration year which is five or ten years back. This eventuality is indicated by the horizontal arrow pointing to the left in **Figure 3.3**, where the Validation Year transport model is established first, and the Calibration Year transport model is derived by modifying network and services coding between the Calibration Year and the Validation Year based on the main known changes in the transport system. For the Calibration Year model, the land use and transport models are iteratively run based on observed congested speeds in the transport network.

A time lag between changes in the transport cost matrix and chances in land use is applied to the current year transport model, as not all location decisions are made instantaneously to the changes of transport cost. For a future year policy run, there are two possible ways to represent the interactions between land use and transport. First, a future policy year can be run with inter-temporal cost averaging as in '**Future Year 1**' – typically this is for a medium term horizon; model outputs from such a run indicate the most likely land use pattern based on time-lagged land use decisions. Secondly, the land use and transport models can be run iteratively till a stable solution is reached for a future year, as shown for '**Future Year 2**'; this is applicable, for example, where the long term equilibrium solution is of policy interest.

3.2.4. Operate with MEPLAN

The integrated LUT model has been built upon MEPLAN software package, which provides with a flexible modelling framework (ME&P, 1989; Abraham, 1998; Abraham and Eng, 1998). The license of MEPLAN has been granted for this study by the WSP Group in Cambridge.

The relevant MEPLAN programs are described as follows:

(1) LUS: the land-use model, which estimates the spatial patterns of employment and household, and derives movements between zone pairs. The embedded trip distribution module generates trip matrices.

(2) FRED/DERF: the interface bridges the land use and transport. It converts generalised travel costs from transport model into zone-to-zone accessibility for use in the land use model; in return, it provides the transport model with peak-hour trip matrices by traveller type, which are calculated by the resulting matrices from land use model.

(3) TAS: the transport model, which implements the modal split and traffic assignment. Specifically, it segments trip matrices by different modes and then assigns the segmented trip flows (vehicle or person) onto the modelled networks. Rail over-crowding has not been applied in the Greater Beijing model, mainly due the lack of appropriate data for capping capacity. For road network, the conversional interactive process of capacity restraint has been replaced by the congestion-condition link speeds calculated from the GPS trajectory data.

The linkage between land use and transport over time has been incorporated through the operation which is shown in **Figure 3.4** (Williams, 1994).

As seen, the MEPLAN **LUS** (land use model), **FRED** (transformation) and **TAS** (transport model) programs run progressively through different time periods. Whereas the time interval, ***Δt*,** represents the time allowance for boom and bust fluctuations in the economy to balance out, and can be set by modellers based on the regional context and policy concern. The modules under the heading "**Period…**" set out evolutionary progresses that happen slowly through time, for instance, the construction of dwellings and road infrastructures. The modules under heading "**Time…**" represent the processes that adjust more quickly, such as the trip generation. Links between disparate modules represent information flows as follows (Williams, 1994):

- The horizontal arrows, that go from one time period to the next, indicate the continuity in the existing stock of infrastructure and the inertia in the historical patterns of households and employment locations.
- The vertical arrows, that go from **LUSA** (land use) through **FRED** (interface) to **TASA** (transport), indicate that the demand for transport is a reflection of pattern of land-use activities and their interactions between land use and transport at a particular point of time.
- The angled links represent interactions between land use and transport. The diagonal arrows that go from **TASA** through **FRED** to **LUSA** represent impacts on land-use patterns from changing transport conditions.
- The dashed link from **TASA** going backwards through time to **FRED** denotes the averaging of the current travel costs with those of the previous time period.

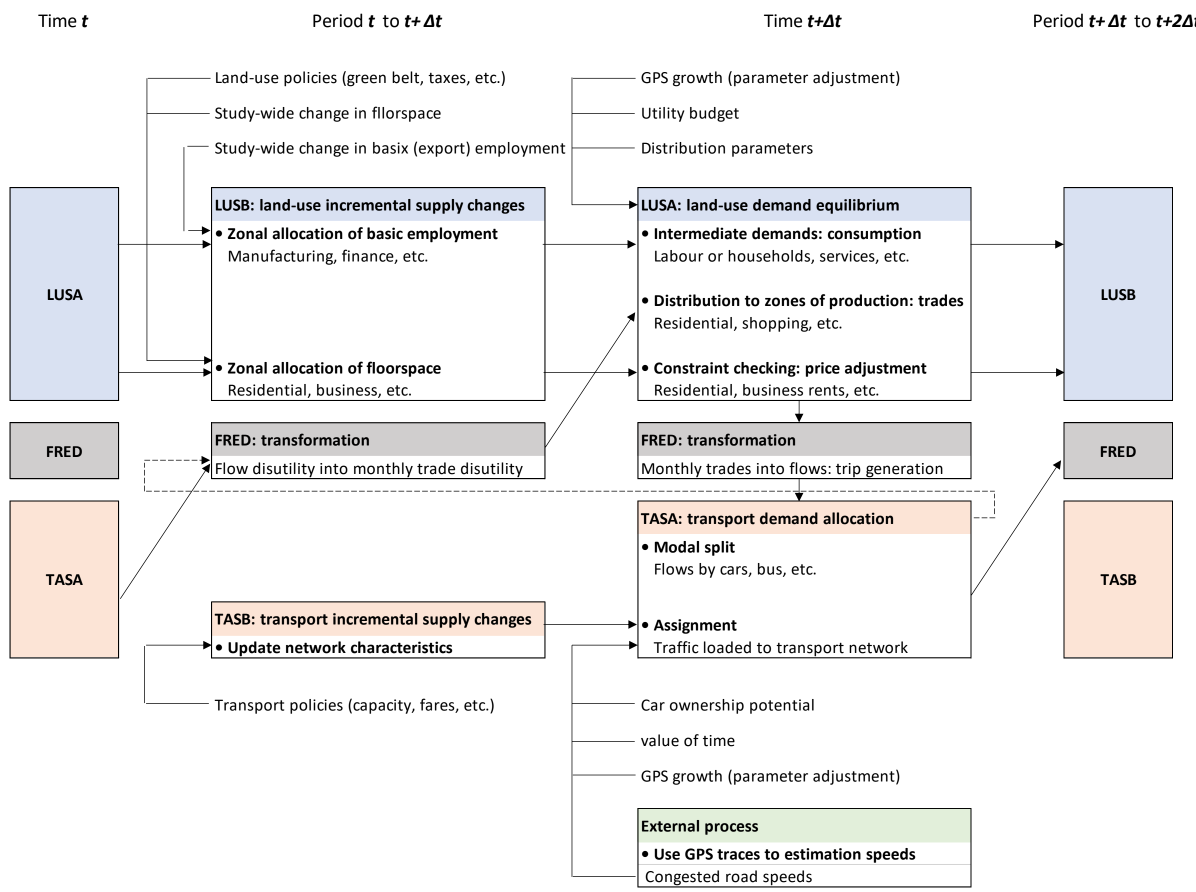


Figure 3.4. The linkage through time in the MEPLAN model
Reference: <Williams, 1994>

3.3. Model components

3.3.1. Regional economy and land use models

3.3.1.1. Model structure

Besides the strategic transport model, the whole model is also driven by another two engines, including a regional economy model and a land use model. The regional economic model has been developed based on the recursive spatial equilibrium (RSE) approach, which aims to represent the spatial economic mechanism in mega-scale regions where encounter fast-paced changes, predicting the possible outcomes of major policy interventions and urban dynamics (Jin et al, 2013; Wan, 2016). It interacts with the MEPLAN-based land use model, which as mentioned in the **Section 3.2.2**, simulates the land use activities through Steps **(1)** to **(4)**, providing the strategic transport model with the commuting and non-commuting trip OD matrices (as seen in **Figure 3.2** in **Section 3.2.2**).

3.3.1.2. Input

As illustrated in **Figure 3.1** (**Section 3.2.1**), both of the RSE model and the land use model require input passed from the strategic transport model: accessibilities, or travel costs and times for desired time period between all zone pairs.

3.3.1.3. Formulation

There are three elements in the land-use model which are most relevant to the strategic transport model, including **(1)** spatial distribution of employed residents, **(2)** spatial distribution of for non-commuting trips, and **(3)** conversion of production-attraction matrices to OD matrices. Here we briefly introduce the formulation of these relevant modules. For detailed formulation, please refer to works such as Jin et al (Jin et al, 2002) and Wan (Wan, 2016) for the RSE model, and to works such as Jin et al (Jin et al, 2017) and Rong (Rong, 2016) for the land use model.

- ***Spatial distribution of employed residents***

This step allocates the employed residents to model zones based on a logit-based discrete choice function as follows (Jin et al, 2017; Jin et al, 2002; Rong, 2016):

$$T_{ij}^{m} = T_{j}^{m} \frac{S_{i}^{m} e^{-\lambda^{m}(c_{i}^{m}+d_{ij}^{m}+r_{ij}^{m}+w_{i}^{m})}}{\sum_{i} S_{i}^{m} e^{-\lambda^{m}(c_{i}^{m}+d_{ij}^{m}+r_{ij}^{m}+w_{i}^{m})}} \qquad \textbf{Equation 3.01}$$

where,

T_{ij}^{m} is the trade flow of employed residents by type m from production zone i to consumption zone j. T_{j}^{m} is the total number of demanded employed residents.

S_{i}^{m} is a size term which represents the number of households.

The utility term consists of four variables: c_{i}^{m} is the cost of living net of commuting; d_{ij}^{m} is the generalized cost of commuting including out-of-pocket travel costs, travel time, and other perceived disutility of travel; r_{ij}^{m} is a constant that represents impedances over and above d_{ij}^{m}; and w_{i}^{m} is a constant subject to calibration. λ^{m} is the concentration parameter.

- ***Spatial distribution of for non-commuting trips***

Non-commuting trips are distributed by a similar logit-based discrete choice model as follows:

$$T_{ij}^{m} = T_{j}^{m} \frac{S_{i}^{m} e^{-\lambda^{m}(d_{ij}^{m}+w_{i}^{m})}}{\sum_{i} S_{i}^{m} e^{-\lambda^{m}(d_{ij}^{m}+w_{i}^{m})}} \qquad \textbf{Equation 3.02}$$

The symbols are similarly defined as in **Equation 3.01**, but only with m representing different trip purposes.

Secondary local service trips, such as education and retail trips, give rise to local service employment demand Y_{j}^{m}:

$$Y_{j}^{m} = a^{mn} \sum_{j} T_{ij}^{n} \qquad \textbf{Equation 3.03}$$

This employment will in turn generate its own demand for employed households, and so on (Jin et al, 2002).

- ***Conversion of production-attraction matrices to OD matrices***

The monthly travel demand matrices in Production-Attraction format are then converted into Origin-Destination format for a typical weekday morning peak. For commuting trade flows, the conversion follows the equation below:

$$F_{ij}^{k} = \sum_{m} \Phi^{mk}\left(\alpha_{ij}^{m} T_{ij}^{m} + \omega_{ji}^{m} T_{ji}^{m}\right) \qquad \textbf{Equation 3.04}$$

Where, AM trips F_{ij}^{k} by type k from zone i to j, include both outwards trade flows $T_{ij}^{m}$and the inwards return flows T_{ji}^{m}. α_{ij}^{m} and ω_{ji}^{m} are the respective proportions of outwards and inwards return trips to be loaded to morning peak. Φ^{mk} represents the average trip rate per employed resident m.

For non-commuting trips, the conversion is similarly formulated as:

$$F_{ij}^{k} = \sum_{m}\left(\alpha_{ij}^{m} \delta^{mk} T_{ij}^{m} + \omega_{ji}^{m} \delta^{mk} T_{ji}^{m}\right) \qquad \textbf{Equation 3.05}$$

where δ^{mk} converts monthly trips into an average number of trips for the morning peak in a typical weekday.

3.3.1.4. Output

The output relevant the strategic transport model from these two modules is the distribution of trips in the format of OD matrices.

3.3.2. Strategic transport model

3.3.2.1. Model structure

The strategic transport model is the focus of this thesis. It aims to estimate patterns of traffic flows from a macroscopic point of view in the study area. The transport model is made up of a multimodal transport network and a set of functions regarding the characteristics of local transport (e.g. fares). It diffuses the demand OD trip matrices generated by the land use model onto the multimodal transport network through **modal split** and **network assignment**.

The basic structure of the model follows the established ones such as Jin et al (Jin et al, 2002) and Williams (Williams, 1994). But the use of congested road speeds, which are estimated from the taxi GPS traces in Beijing for workday AM peak in February 2008, have improved the efficiency in establishing and calibrating the model, demonstrating an approach to combine the new crowdsourced data with the conventional transport modelling.

3.3.2.2. Input

As seen from **Figure 3.1** (in **Section 3.2.1**), the strategic transport model mainly requires five input data sets, including:

(1) OD matrices by trip purpose by traveller type: these are the estimated demand of origin-destination person trips provided by regional economic and land use models (Rong, 2016; Wan, 2016). Freight flows are not modelled mainly due to the unavailability of calibration and validation data.

(2) Multimodal transport services: consist of modelled links and nodes for modelled transport networks, and the characteristics of their services (such as road link type and corresponding capacity).

(3) Congested road speeds and average speeds for rail travel: congested road speeds and average time-table rail (e.g. metro and rail) speeds are used directly in the model, instead of the speeds resulted from the conventional iterative progress of capacity constrain.

(4) Public transport fares and fuel prices: which are used to establish the generalised costs in the calculation of disutilities.

(5) Fuel consumption function: which is applied to reflect the variance in travel costs that caused by the different level of fuel consumption.

3.3.2.3. Formulation

- ***Modal Split***

The purpose of the modal split is to estimate the proportion of the modelled traffic flows F_{ij}^k by mode h, from zone i to another zone j for a specific traveller type k. The model is a logit based hierarchical discrete choice model of the basic form as follows:

$$F_{ijh}^k = F_{ij}^k \cdot \frac{e^{-\lambda^k \cdot u_{ijh}^k}}{\sum_h e^{-\lambda^k \cdot u_{ijh}^k}}$$ **Equation 3.06**

where, λ^k is a parameter; u_{ijh}^k is the disutility function, compromising four different elements, including the out-of-pocket travel cost c_{ijh}^k converted into standard time units through the marginal utility of money ϕ^k, travel time t_{ijh}^k, destination disutility ρ_{jh}^k (such as parking charge), and the mode-specific constant Ω_h^k (Williams, 1977, 1994; Jin et al, 2002).

$$u_{ijh}^k = \phi^k c_{ijh}^k + t_{ijh}^k + \rho_{jh}^k + \Omega_h^k$$ **Equation 3.07**

The travel time t_{ijh}^{k} is the total journey time, including all transfer, waiting, and in-vehicle time, along the network links and nodes comprising the minimum path. Different values of time may be applied to different stages z of the journey.

The hierarchy of modal choice, in either nested or flat logic forms, needs to be built up through trial and error with consideration of the data availability for modal calibration and validation.

Besides estimating number of flow volumes by each mode of transport, the model also revises the average monetary costs, travel times and disutilities between all zone pairs for each type of travellers. This information, converted into disutilities per trade unit, is fed back to the land use model for the next time unit, being the measures of accessibilities among zones which influence the future spatial choices (Williams, 1994).

- ***Network Assignment***

Following the modal split, the by-mode traffic flow is converted into vehicle unit and then assigned onto the network links. The network assignment model adopts a stochastic Dial-type user equilibrium algorithm (Jin et al, 2002; Williams, 1994; Dial, 1971). It is based on random utility theory with a logit form as follows:

$$T_{ij}^{p} = T_{ij} \frac{e^{-\lambda_{ij}^{p} \cdot g_{ij}^{p}}}{\sum_{p} e^{-\lambda_{ij}^{p} \cdot g_{ij}^{p}}}$$ **Equation 3.08**

where,

T_{ij}^{p} is the resulting traffic flow that travelling along path p from origin zone i to destination zone j. T_{ij} is the total traffic flow from i to j.

λ_{ij}^{p} is calculated based on $\lambda_{ij}^{p} = \lambda / d_{ij}^{min}$, where λ is the parameter which controls the probability of choosing a sub-optimal path, and d_{ij}^{min} is the shortest path or minimum-cost path between i and j.

g_{ij}^{p} is the utility term, which is represented by a generalised cost function as:

$$g_{ij}^{p} = d^{p} \cdot c_{d}^{p} + f^{p} \cdot c_{n}^{p} + t^{p} \cdot c_{t}^{p} \cdot (1 + \delta) \cdot \nu^{p}$$ **Equation 3.09**

with d^p as the distance of path p, value of distance c_d^p, flow volume f^p, value of network cost c_n^p, journey time t^p, value of time c_t^p, difficulty or perception parameter δ, and link-and-mode dependent value of time ν^p for path building.

It assumes that vehicles are more likely to use the least disutility path than to use other competing paths, but some vehicles may use other paths with larger utilities (Williams, 1994). The assignment can also be run with an all-or-nothing mode if required (e.g. for testing the transport networks), which allocates all traffic along the path with the least disutility.

Due to the unavailability of timetables for local public transport service, the same algorithm has been applied to both the road and public-transport traffic flows but on respective networks.

3.3.2.4. Output

The main outputs from the strategic transport model include: **(1)** trip matrices by user mode by trip purpose or type in either Origin-Destination or Production-Attraction format (or both); **(2)** travel costs or times between zone pairs over the desired time period(s), which are fed back to the regional economy and land use models, making an impact on the locational choice behaviours for the next iteration; and in addition **(3)** statistics, quantum and maps for further analyses and assessment.

3.4. Incorporate with new data sources

Whilst this dissertation makes incremental changes to established modelling frameworks, it aims to make substantially new contributions to operationalising the calibration of the strategic transport model, which is generally the bottleneck for model building and model application in terms of the substantial needs for project time and man-power resources. Of all the main transport model development tasks, the most challenging for establishing a new model seems to be **(1)** develop, finetune and validate the multimodal transport networks for each modelling year; **(2)** identify the patterns of congestion, especially the hotspots of slow moving traffic, in order to gain an in-depth understanding of the nature of congestion; **(3)** estimate the congested traffic speeds where they are substantially different from network free-flow speeds, such as during the peak periods, with a comprehensive coverage of the congested areas; **(4)** complete transport network modelling by supplementary intra-zonal transport networks – the intra-zonal transport costs are of little practical significance to conventional transport models, but for land use modelling, they are of equal importance to inter-zonal transport costs. Furthermore, an appropriate handling of intra-zonal networks and travel costs can help to reduce the pressure completing the transport model to be set up with numerous small zones at the beginning phase of the model development; the benefits are obvious: numerous small zones not only increase the data hungriness of model development, they also impose a massive task for network checking and finetuning which are more appropriate for later phases of model enhancement.

In this section, we present a novel approach to each of the four tasks above.

3.4.1. Multimodal network creation

It is somewhat surprising that given the fast development of GIS platforms and online resources on transport services that a large number of cities in the emerging economies do not yet have readily available transport network data that can be used as inputs to model network building. For example, Beijing is one of the cities with various good GIS and mapping data capabilities within specialist government agencies which are better than most emerging economy cities, but there is no publicly available digital database of its road network that are provided by those government agencies. Other transport networks (such as urban metro network, railway networks) are experiencing a similar situation.

Even if such data were provided, the data on geographical configuration of the network links would be found in separate datasets from the information on link service capacities or user charges, because they are managed and administered separately. Major online search engine providers such as Google and Baidu (in China) have been developing online mapping and directions service, although the underlying data is not publicly available.

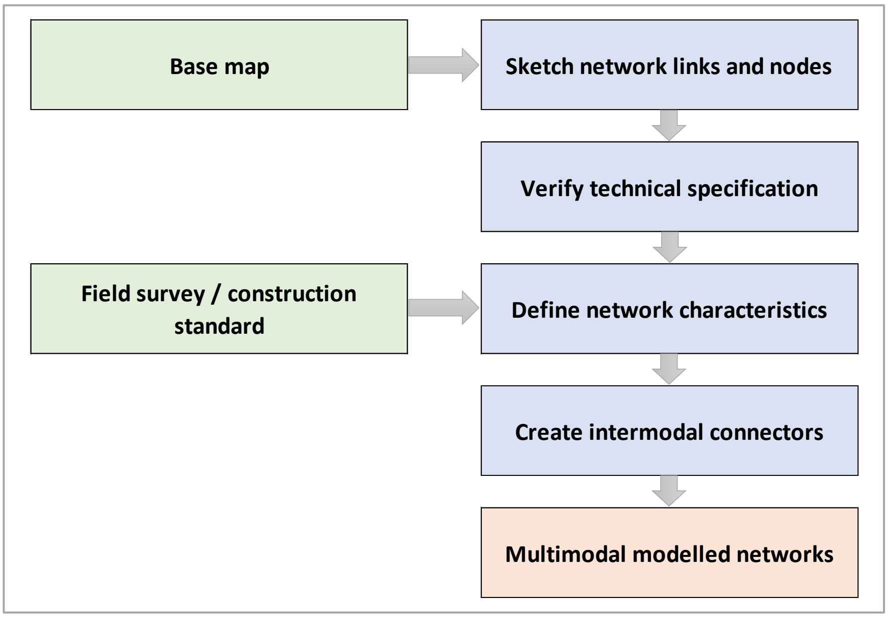


Figure 3.5. Processing steps of multimodal network creation (base year)

Here we consider the generic methodological issues within the development of model networks that are suitable for incorporating new, smart transport data sources (**Figure 3.5**).

In a city that does not have a readily available digital-form transport network, the first step would be to procure or less preferably, establish from scratch a reasonable set of network links for road, metro, railway, dedicated cycleway and footpath. In this context, the on-going development of online mapping (such as the Open Street Map or OSM) has become an important source of near universal coverage of transport network data, particularly for urban roads. For instance, in Beijing we have compared several sources and found that the coverage of the OSM is actually better and more up to date than published hardcopy maps. We have also examined several Chinese cities and found this to be true as well. This suggests that the OSM could in many instances be a reasonable starting point base map for model network building.

The second step is to verify the technical specifications of this digital base map. For instance, is the resolution and geo-coding accurate enough to be used in conjunction with transport smart data, such as GPS traces of road vehicles? Is there a detailed representation of the complex topological structure of the real road network (such as directions, overlaid turns on bridges or tunnels etc.)? Especially the road and expressway network are suitably detailed to accommodate a map-matching method that can facilitate the identification of traffic delays and the estimation of network speeds. For GPS traces, this must include detailed representation of multi-lane and multi-directional network links and complex junctions. Availability of detailed modelled networks is often a restriction as such datasets are often costly or not readily available. There are also issues with topological validity, whereby networks have not been developed with modelling in mind, and there have been topological errors, such as undershoots, overshoots and misconnection on links. Despite the high accuracy of the manually generated road network, the level of detail (particularly the completeness of its coverage) is not high enough to accommodate the requirements of the proposed map-matching approach. To address this issue, we have developed a geo-processing model to examine the network connectivity and enrich the network with 'infill' links, e.g. unclassified road links, Hutongs (narrow streets or alleys often found in North China) and parking accesses etc.

The third step is to define the characteristics of networks, such as the link type (e.g. a variety of urban roads and expressways, metro lines, railways and high-speed railways), link length, capacity, free-flow speed and opening year (e.g. for networks with major changes among different model years).

The final step is to create intermodal connections between the modal networks, so that they reflect the connections that make an integrated multimodal transport network for urban travel.

3.4.2. Microscopic GPS Trace Data Analysis

The second task investigates the vehicle GPS trace data to understand the patterns of road traffic represented by it, for the purpose of verifying the level of appropriateness of applying the data to the estimation of congested link speeds.

It first helps to identify possible noises and miscoding in the data which is always possible with any dataset, but is particularly the case with massive, automatically recorded data. The investigation helps to ascertain the quality of the information contained in such a dataset.

Secondly, we analyse the data to identify the hotspots of slow-moving traffic, which could result from service operations (such as taxis and buses at stations or other loading/unloading areas) or road congestion. This analyse will visualise the level and location of traffic operations and congestions, making them comparable with our local knowledge.

As reviewed in **Chapter 2**, there are many different approaches to analyse the clustering and density of moving vehicles. Here we focus on developing a method that builds on the generic DBSCAN algorithm (Ester et al, 1996; Kriegel et al, 2011). This is because the DBSCAN-based algorithms appear to be more suitable to the analysis of a priori unknown number of moving vehicle clusters in different sizes and shapes, and are capable of coping with a considerable degree of noise (Tran et al, 2012). It is also more flexible with the geometric shapes of the clusters, e.g. a cluster surrounded by but not connected to a different cluster. Owing to the use of the *minPts* parameter in DBSCAN, the cluster analysis is less prone to noises that are generated by an accidental single link connecting different clusters, and thus are more robust to outliers. Such clustering and density analysis would be more challenging to implement, for instance with methods such as k-means or Gaussian mixture EM clustering.

The DBSCAN approach has been applied to transport problems, e.g. the distribution of road accidents (for the latest methods, see Kapp, 2015). It has also been used experimentally for moving vehicle clusters (e.g. Diker et al, 2012; Han et al, 2013). Here we further develop the method so that it can be used to identify vehicle movement patterns by time period, and further to inform the planning and management of traffic operations. This is because, despite some criticisms towards DBSCAN regarding border density and intrinsic cluster structure (Sculley, 2010), the algorithm has two basic advantages in processing the large-scale one-the-road GPS signals from moving vehicles. Firstly, DBSCAN permits clusters in arbitrary shapes. For geographical data that potentially contain very different traffic and road configurations, this feature is very crucial, as it permits the approach to produce clusters based on the density of complex and irregular-shaped road networks. Secondly, the method is relatively simple and transparent for explaining to non-specialists, which enhances the usability of the analysis outputs when engaging with operation managers and planners.

As reviewed in **Chapter 2**, DBSCAN is a density-based clustering algorithm. It would be useful to spell out the concepts of DBSCAN for the development of our method. As Ester et al (1996) proposed four crucial definitions of DBSCAN when detecting clusters in database D:

1. The ε-*Neighbourhood* set (N_ε) of a point p, i.e. $N_\varepsilon(p) = \{q \in D \mid dist(p,q) \leq \varepsilon\}$. ε is the radius of search distance (circles in **Figure 3.6**). The minimum number of points (*MinPts*) in an ε-*Neighbourhood* set is also required to initiate the approach;
2. Directly density-reachable: a point p is directly density-reachable from a point q wrt. ε and *MinPts*, if (1) $p \in N_\varepsilon(p)$; and (2) $|N_\varepsilon(p)| \geq MinPts$ (core points condition);

3. Density-reachable: a point p is density reachable from a point q wrt. ε and $MinPts$, if there is a chain of points $p_1, p_2, \ldots, p_n$ ($p_1=q$, $p_n=p$) such that p_{i+1} is directly density-reachable from p_i ($i=1, 2, \ldots, n-1$);
4. Density connected: a point p is density connected to a point q wrt. ε and $MinPts$, if there is a point k such that both p and q are density-reachable from k wrt. ε and $MinPts$.

Note that the relationships above among directly density-reachable points are symmetrical, but the relationships between indirectly density-reachable points are not. All directly and indirectly density-reachable points are density-connected among themselves.

Thus, it is capable to define a cluster in a density-base notion as a set of density-connected points with maximal density-reachability. Noise is then simply defined the set of points in D not belonging to any of its clusters (Ester et al, 1996).

More precisely speaking, let D be a database of points. A cluster C wrt. ε and $MinPts$ is a non-empty subset of D satisfying the following condition (Ester et al, 1996; Campello et al, 2013):

1. Maximality of density-reachability: $\forall p,q$: if $p \in C$ and q is density-reachable from p wrt. ε and $MinPts$, then $q \in C$;
2. Density connectivity: $\forall p,q \in C$: p is density-connected to q wrt. ε and $MinPts$.

Let $C_1, C_2, \ldots, C_m$ be all the clusters of database D wrt. ε_j and $MinPts_j$ ($j=1, 2, \ldots, m$). Then the noises are defined as the set of points in D not belonging to any cluster C_j, i.e. $Noise = \{p \in D \mid \forall j: p \notin C_j\}$.

For example, in **Figure 3.6**, if we define the $minPts = 2$, then the green points form the core of the cluster; as all green points are directly density-reachable to at least the minPts number of other points an ε radius. The blue points B_1 and B_2, on the other hand, have only one directly density-reachable neighbour points, but density-connected to other green points, so they form the periphery of that cluster. The red point N is not within the radius ε of any points in this cluster and is thus not part of the cluster. It is useful to point out that even the red point is within and only within the radius ε of the blue points it is still not part of the cluster – this definition avoids the tenuous 'single-link' connectivity that could cause the coalescence of clusters due to noise and imprecision in the data.

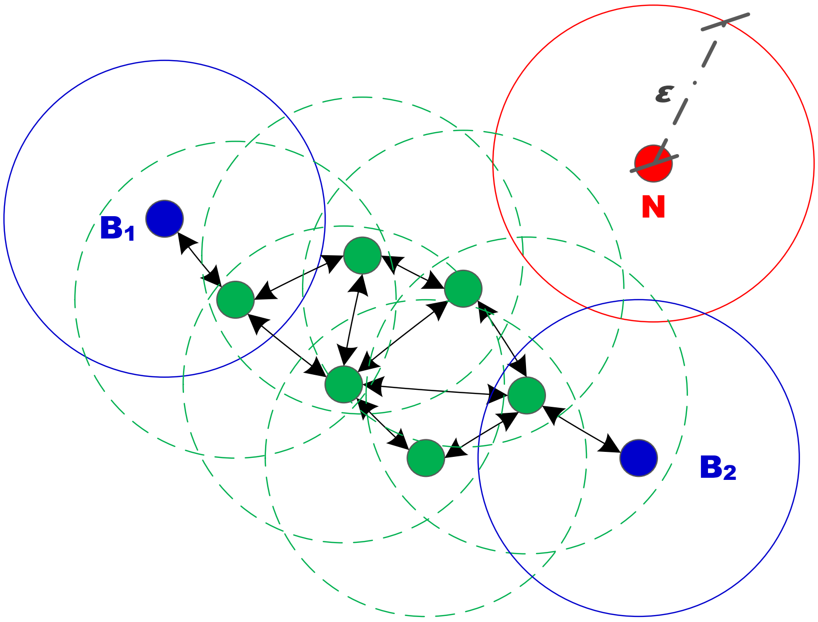


Figure 3.6. An example of clustering progress of DBSCAN Algorithm

For our analysis, the DBSCAN algorithm is intended for use in identifying the locations and shapes of moving vehicles, particularly those which are slow moving and thus form clusters in one way or another. The reasons may be traffic congestion, traffic accidents, queues behind red traffic lights, passenger-related activities (such as picking up or unloading), technical services of the vehicle (such as refuel or repair) etc. To identify and understand the evolution of such cluster patterns of taxis slow-moving and stopping hotspots would provide insights into the road traffic status in a way that has not been possible in the past.

In anticipation of the GPS taxi traces with relatively low sampling rates from Beijing, which will be our data for the case study in **Chapter 4**, we develop two core procedures: the first one is to process and explore the raw GPS signals, and the second one is to identify vehicle clusters for different time periods in line with the traffic operation management time cycles, particularly during and around the morning peak hours when road capacity is subject to the sharpest rises and declines of congestion.

The process of the raw taxi GPS footprints constitutes two stages.

At the first stage, the sequential footprints of each taxi are articulated into traces, which are generated from one GPS signal to the next from the vehicle in questions, in the form of straight lines. Singleton signals are excluded. These traces are loaded into ArcGIS and shown as link-shapes with attributions of link identifier, length, start-point's timestamp and endpoint's timestamp etc. for a visual check.

The second stage of analysis cleans the raw data, which is aided by the visual inspection. We carry out a series of logical checks to exclude signals that are generated erroneously, for instance a sequence of signals with different longitudes and latitudes, but all signals showing the same time stamp. In the view of the relatively low signal sampling rates, we also exclude the pair of signals too far apart (say the Cartesian distance being more than 500m). This is because the data cannot provide directly usable information regarding their trajectories for clustering analysis if the start point is too far from the end point (however, we do make use of such low sampling rate data with the aid of an estimation of their most likely paths for the purposes of link traffic speed estimation – see next subsection below). This distance range filter is to retain links with a comparatively higher sampling frequency, as both start point and end point of each link are in the vicinity of each other. Note this is in line with our aims to investigate slow moving traffic.

To account for the imprecision of the crow-fly links between the start and end point pairs representing the actual vehicle trajectory on the road networks and parking facilities, we further develop a vertex-generating procedure. This procedure is implemented to insert vertices for each crow-fly link for every 10-metre distance. The design of this step is based on the theoretically density-based concept of the DBSCAN algorithm, and is aimed to give equal and fair opportunity of each link to be recognised by the DBSCAN clustering process. Each processed vertex inherits the feature from its host crow-fly link, including the start-point and end-point timestamps, and the implied duration of the movements in between.

3.4.3. Estimation of Congested Link Speed

The third key task to establish a new strategic transport model for a city with significant traffic congestion is to obtain a comprehensive coverage of congested road speeds. This task was impractical before massive vehicle trajectory data became available. So far, the vehicle trajectory data have been used to define fairly wide congestion speed ranges, such as being publicised in online and street corner traffic congestion maps. For strategic transport modelling a more precise estimation of the link speeds would be required.

Here we develop a method that is robust enough in dealing with relative poor-quality GPS vehicle trajectory data, which is typical in the emerging economy cities (for an example, see the data from Beijing in Chapter 4). The data quality is poor because the GPS signals have imprecise geo-locations and the frequency of signals are relatively sparse. This essentially requires a robust map-matching algorithm that can map the GPS signals onto the road network.

Most map-matching algorithms map current or neighbour locations to the road network. The accuracy is generally low as the map-matching routine generally only considers current position of the vehicle, ignoring the information regarding the previous and subsequent locations of the vehicle. Furthermore, these traditional map-matching algorithms rely on high sampling rate frequency and become much less reliable as the uncertainty in data increases (Lou et al, 2009).

There have been emerging methodological developments that aim to infer paths from sparse GPS observations using estimated shortest network paths (Lou et al, 2009; Rahmani and Koutsopoulos, 2013; Patterson et al, 2003; Fadaei Oshyani, 2011). However, they tend to adopt a distance-based minimum paths, which have been shown to be unrealistic when compared with actual routes. A study in London using a GPS vehicle trajectory dataset from taxis has shown that the estimations using a distance-based minimum paths could predict on average around 40% of the actual route travelled (Manley and Dennett, 2018; Manley, 2015; Mazur and Manley, 2016).

Here we build on the method first proposed by Rahmani and Koutsopoulos (2013) and develop an enhanced algorithm that can be iteratively applied to estimate and refine the paths and congested speeds estimations. We will further subject the algorithm to rigorous validation tests in the applications.

The estimation problem can be generically presented as follows. The network consists of a set of one-way and bi-directional links R^m. Each link consists of a set of link vertices $R^1 \rightarrow R^2 \rightarrow \cdots \rightarrow R^n$ representing the geometry of the link. Each link intersects a junction node N at either end. Each link is connected to adjoining links by a node. Each link contains known information on link type $c_{R^m} = f(R^m)$, free flow speed s'_{R^m} and length l_{R^m}. As such the travel time t'_{R^m} for each link, where the freeflow speed can be expressed as $t'_{R^m} = l_{R^m}/s'_{R^m}$. Each link is assigned a tolerance buffer b_{R^m} associated with its link type as in **Equation 3.10**.

The taxi trajectory consists pairs of sequential taxi locations. Each pair of locations therefore consists of a start-point P^1 and endpoint P^2. Each point has its location coordinated $(x(P^n), y(P^n))$ and a timestamp of the GPS signal $T(P^n)$. Each such trajectory component can therefore be described as $T: P^1 \rightarrow P^2$ and the observed time difference between the consecutive points is $T(P^2) - T(P^1)$.

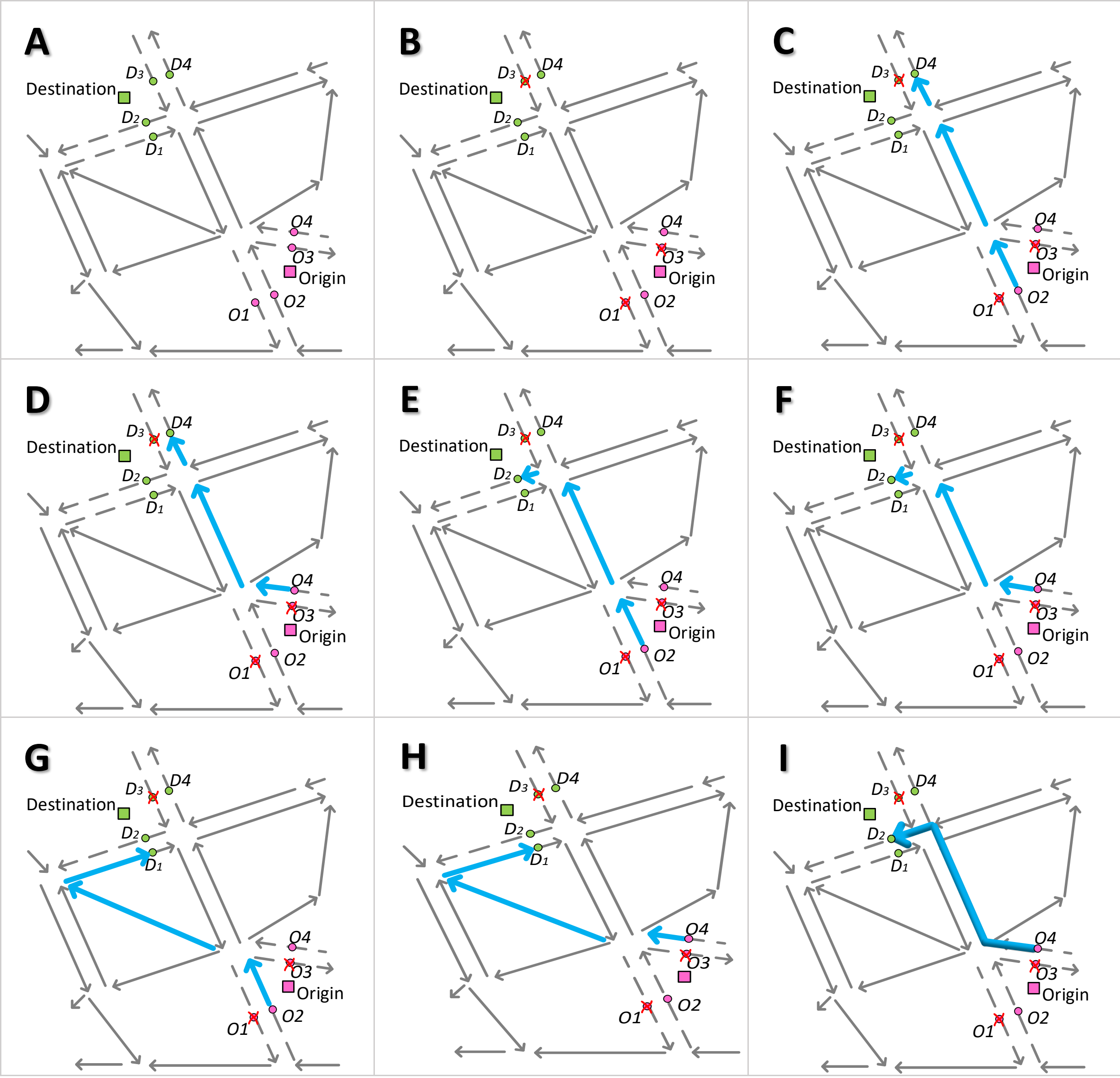


Figure 3.7. Steps within one iteration of the map-matching algorithm

Source: <Deng et al, 2015>

Note: <1. For each pair of GPS points on a trajectory from the Origin point (marked in the map by a pink square) to the Destination point (a green square), the map matching algorithm finds all candidate start road links $\boldsymbol{CsL}^{n}$ *and end links* $\boldsymbol{CeL}^{n}$ *within the appropriate distance buffers* $\boldsymbol{b}_{R^m}$ *and the vertices on the candidate road links that are the nearest to the GPS points are identified as the start and end points (marked as small pink and green dots espectively with notation* **On** *for origin cross-sections and* **Dn** *for destination cross-sections, where* ***n=1,2,…,n*** *is a serial number);*

2. Frame **(B)***: rule out the on-link vertices that are infeasible for the trajectory movements (in the map, these points are crossed out with a red cross on the top);*

3. Frames **(C-H)***: for each possible* **On** *to* **Dn** *pair, calculate the minimum path based on car travel time on road;*[1]

4. Frame **(I)***: in the case of the Beijing data, experimentation suggests that the* **On** *to* **Dn** *pair that has the shortest travel car time should be selected as the estimated trajectory path on the road network.>*

Although in a majority of cases it is obvious from which road links the GPS trajectory points belong, in dense urban networks there can be some ambiguities, particularly where the GPS signal locations deviate from their true emitting locations which often occur with the signals

[1] The time traversing each of the links is, in first instance, based on free flow car speeds. The initially estimated congested speeds are then fed back to the network for next iteration of the algorithm, i.e. iteration k uses the link speeds estimated at iteration $k-1$.

available to civilian use. To make effective use of the GPS trajectory data, it would be necessary to develop a robust algorithm which can deal with such ambiguities. Building on existing literature we propose the following algorithm. The algorithm aims to map the GPS trajectory signal points onto the road network, find all potential start and end locations pairs, select from them the most probable pair of vertices on the road links, and, given the selection, estimate the link speeds.

The first step therefore is for the algorithm is to allocate each of the trajectory points (e.g. P^1 and P^2) to all possible locations on a network road links (i.e. the vertices along $R^1 \rightarrow R^2 \rightarrow \cdots \rightarrow R^n$). Our proposed solution algorithm is to generate first candidate start CsL^n and end links CeL^n for each trajectory. The candidate links are all links within a search buffer b_{R^m} around the trajectory points P^1 and P^2. Candidate start vertices CsP^n and end vertices CeP^n are identified as the nearest points on each candidate link (**Figure 3.7 A**).

Here we define the tolerances of the search buffer as follows:

$$b_{R^m} = \left(d_l\left(f(R^m)\right) x\, n_l(R^m)\right) + \left(d_s\left(f(R^m)\right) x\, n_s(R^m)\right) + d_u\left(f(R^m)\right) \qquad \textbf{Equation 3.10}$$

where b_{R^m} is the buffer distance of link R^m, $f(R^m)$ is the link type classification function (i.e. it returns the link type of R^m), $d_l\left(f(R^m)\right)$ is the typical lane width for link type $f(R^m)$, $n_l(R^m)$ is the number of lanes of link R^m, $d_s\left(f(R^m)\right)$ is the typical width of central separation band for $f(R^m)$, $n_s(R^m)$ is the number of central separators of link R^m, and $d_u\left(f(R^m)\right)$ is the typical width of the utilities buffer on the sides of link type $f(R^m)$. Note that typically the utilities buffer is wider for the major arterial roads and narrower for the minor streets. This means that the search buffers differ considerably by road link type. Candidate links representing higher class roads will have a wider search buffer. Trajectory signals outside of the defined tolerances will not be considered in the map-matching process below.

The second step is to rule out the on-link vertices that are infeasible for the trajectory moments (e.g. those leading to the opposite direction) through checking the permitted direction of the road links (**Figure 3.7 B**).

The third step is to identify the minimum paths by travel time for each possible pair start and end vertices. The selection of minimum time rather than minimum distance is based on the fact that in congested urban road travel, cars (especially taxis) tend to choose the routeing to minimise travel time rather than distance (**Figure 3.7 C-H**).

The fourth step is to select among all the possible start and end vertices pairs. Many alternative selection criteria are possible and the choice among them is essentially an empirical matter. For instance, in the Beijing application reported in Chapter 4, various experimentation shows that the vertices pair that yields the smallest travel car time (**Figure 3.7 I**) produces the results closest to the observed data in the validation procedure. However, other criteria could be relevant in other cities or datasets. The selection of the vertices pair provides an estimation of the distance and travel time which implies an average speed from the start vertex to the end one, which could involve travelling on several road links.

The fifth step is to estimate the likely congested speed for each road link involved, given the implied average travel speed between the start and end vertices worked out in Step 4 above. This requires a proportion of the total start-end trajectory travel time is allocated to each link. This is initially allocated pro rata based on the ratio of free flow travel time on each link to the overall start-end travel time. Since the algorithm is run iteratively (see step 7 below), this can be more generally defined as time allocation pro rata based on the ratio of the previous iteration's travel time on each link to the overall start-end travel time. Therefore, in the case of start trajectory points P^1 and end point P^2 which are map-matched above to successive road links $R^1 \rightarrow R^2 \rightarrow \cdots \rightarrow R^n$, the estimated time of traversing link R^k after iteration k the pair of successive trajectory points P^1 and P^2 will be:

$$t_k^{P^1 \rightarrow P^2}(R^m) = \left(T(P^2) - T(P^1)\right) \cdot \frac{distance_k(R^m)/speed_{(k-1)}(R^m)}{\sum_n distance_k(R^n)\,/speed_{(k-1)}(R^n)} \qquad \textbf{Equation 3.11}$$

where $T(P^1), T(P^2)$ are the timestamps for the successive GPS points P^1 and P^2, $speed_{(k-1)}(R^m)$ is the speed estimation for link R^m produced by iteration $k-1$, and $distance_k(R^m)$ is the overall length of the selected path from P^1 to P^2 as obtained from the current iteration k.

The sixth step is to address multiple estimations of link speeds that are obtained from different vehicle GPS trajectory records. The multiple estimations are possible because different vehicle trajectories can overlap, particularly in dense urban areas. As the number of trajectory records accumulate such overlapping estimations will become more common. This makes it feasible derive a statistical distribution of congested speeds for the frequently traversed road links by type of day and time of day, with outputs such as number of estimations, the range of speeds, the mean and standard deviation, etc. relative to the free-flow speed. In the k^{th} iteration of the estimation, the mean congested speed for link R^m is then:

$$speed_k(R^m) = \frac{1}{\|M_k(R^m)\|} \cdot \sum_{P^1 \to P^2 \in M_k(R^m)} \left[{distance_k(R^m)} / {t_k^{P^1 \to P^2}(R^m)} \right] \quad \textbf{Equation 3.12}$$

where $M_k(R^m)$ is the set that contains all the $[P^1, P^2]$ GPS point pairs, for which the selected paths in iteration k traverses road link R^m.

A final, seventh step is to iterate the above process by feeding back the estimated congested road speeds into the calculation of network paths at Step 3. In each iteration, the selection of paths is refined using the estimated link speeds of the previous iteration – initially through benefiting from those trajectory records that can be mapped onto the network without any ambiguity (i.e. with unique vertex pairs in Step 2 and obvious selection of paths), and gradually making use of the refined allocation of link times in Step 3-6.

It is apparent from the above that the noise in the data that arises from the imprecision of GPS data and sparseness of the trajectory signals lead to unavoidable heuristic elements in the algorithm above, particularly in Steps 3 and 4. Such heuristic elements for the present would need to be dealt with through experimentation with specific datasets. We return to this experimentation in **Chapter 4** when testing the algorithm on the Beijing data. Ultimately this can only be improved through obtaining more vehicle trajectory data and collecting more precisely geo-positioned trajectory GPS signals at shorter time intervals.

3.4.4. Intrazonal transport networks

The fourth key task is to develop supplementary intra-zonal transport networks within the strategic transport model. The need for this supplementary network stems from the fact that a transport model cannot assign trips that travel within the zone.

In contrast with detailed road traffic models which are primarily used for relatively short term modelling purposes, a strategic transport model has to consider a wide variety of joint model dimensions, such as land use/transport interaction, multimodal transport systems, more detailed travel demand segmentation and multiple travel time periods. This means that it is not advisable for a strategic transport to start with a large number of small zones like a conventional road traffic model, at least not when building it from scratch. This is because to be burdened with a large number of traffic analysis zones (e.g. several thousand zones at the neighbourhood level) at the beginning will slow down all data collection, assembly and processing tasks that are related to model zones (very often the data at this level is simply not available in emerging economy cities), complicate the checking and verification of the data, and imply very demanding computer requirements. An appropriate handling of intra-zonal networks and travel costs can help to reduce the pressure completing the strategic transport model to be set up with numerous small zones at the beginning phase of the model development; the benefits are obvious: numerous small zones do not only increase the data hungriness of model development, but also impose a massive task for network checking and finetuning which are more appropriate for later phases of model enhancement.

The use of relatively large model zones (e.g. at the urban district or sub urban district level, which would total several hundred rather than several thousands), however, creates a challenge in estimating appropriately the intrazonal travel costs. Intra-zonal transport costs are of little practical significance to conventional road traffic models, which in the main do not include them. But for land use modelling, intrazonal travel costs are of equal importance to inter-zonal transport costs, because the spatial choices cover all possible zone pairs. Intrazonal flows within large zones are very heterogeneous, because the travel modes available for very short distances (such as within walking distance) are not the same as those beyond reasonable cycling distances (e.g. greater than 5kms). The availability of public transport (e.g. the existence of metro services and the frequency of bus services) may also be very different across zones (e.g. zones in the dense urban core vs those in far suburbs). Such heterogeneity cannot be represented by simple intrazonal links that are e.g. characterised by the average distances, speeds and costs that mask the critical differences across the distance ranges implied by sub urban district or urban district level zones.

The purpose of the intrazonal supplementary network is therefore to improve the representation of modal availability and characteristics across the entire ranger of azonal model zone distances, especially where the intrazonal travel distances vary greatly across different flow types, and the zone sizes differ in a marked way in the study area. Here we draw upon the method that was first reported in Jin and Williams (2002) and was later implemented in part of the UK National Transport Model. This is not a widely known method and so far as we are aware it has not been implemented in any emerging economy cities with their different modal availablity, income levels and choice behaviour.

The intrazonal transport network is structured according to a discrete choice model, following the principle that the modal choices are differentiated, simulated, and reported by appropriate distance ranges. From the supply side the average characteristics of modal transport supply are coded by distance range. From the demand side the travel demand within the zone is first split among different distance ranges, and then for each range, modal split is carried out. The intrazonal traffic is not loaded onto the conventional road and rail networks. Instead, the traffic is loaded onto intrazonal network links of different lengths. If the intrazonal distance ranges are defined in a detailed enough way, the modelled travel demand (both intra- and interzonal) can be analysed throughout the entire distance range of the study area.

To set up the intrazonal distance ranges it is necessary to know the geographical size of each zone and that of the built-up area(s) contained within it. This can be obtained from land use map in GIS. Local traffic surveys can provide the average speeds and possibly costs by distance range. In addition, data from local travel surveys are required to calibrate the modal choice behaviours by distance range.

Building on Jin and Williams (2002), we propose the procedure for setting up the supplementary intrazonal transport network in the following steps.

Firstly, a number of standard distance ranges are defined for road travel. The actual number and specification of the distance ranges would depend on local data available. For instance, Jin and Williams (2002) used the UK National Travel Survey (NTS) to define the seven distance ranges used in their transport model. Similarly in an emerging economies city the distances ranges can be defined in accordance with the local travel surveys, in order to benefit directly from the local data for model calibration. Since the travel speeds on roads in the built up areas are usually significantly different from the more sparely populated suburban and rural roads, two types of distance ranges should be defined: i.e. distance ranges within a zone which primarily imply urban travel conditions should be separately identified from those which primiarily imply rural travel conditions. This separation can be defined by zone according to local conditions.

Secondly, the number of distance ranges is defined for each and every zone. This may be facilitated by a GIS interface, where the zone boundaries and built-up areas can be readily available for measurement in terms of the average radius of travel. This shows the relationship of the zone boundaries to the built-up areas. The purpose here is to measure first the radius of the built-up area where spatial interaction is expected to be intense. In some zones this could also apply to a cluster of interconnected built-up areas, in which case the radius of the whole cluster is measured. Or, in other zones, the built-up areas take the form of completely separate towns; in which case the radius of the largest town is measured. The approximate radius of the entire zone is also measured. The radii are then used to determine how many range links will be needed in each zone for both built-up and rural conditions.

The radius of the zone (km) is estimated from the zonal area in square kilometer. The average radius of a zone is calculated from the total zonal area via the relationship between the area of a circle A and its radius *r*, on the assumption that the shape of the zone is a circle. In most cases this assumption is a good approximation. Zones of irregular shapes will have to be individually checked to make sure the radius r estimated is a good representation of the zone.

The radius of the built-up area is similarly calculated, using either of the following methods: **(a)** If there is one distinct built-up service centre, or the built-up areas within a zone cluster together, then the area used in the calculation is the sum of all the built-up segments within the zone. **(b)** If the built-up areas within a zone are dispersed and form separate urban centres, the area of the largest urban centre is used to calculate the radius of the largest built-up area. It follows that the radius calculated from (b) is less than or equal to that from (a). Since very often the built-up areas within a zone are neither uniquely centred nor entirely separated, the appropriate radius would be in between the two values. For this reason each zone will have to be individually examined. In most cases the measure of (a) is found to be a more appropriate measure. In dense urban areas, the radius of the built-up area is equal to that of the zone as a whole, if the zone is totally built-up; or a deduction is made if large parks are present. Where the built-up areas have a degree of separation, a value between the two values is chosen.

Thirdly, for each distance range, intrazonal network links are set up according to modal availability. For road based modes, setting up one road link for each distance range is usually sufficient as cars, buses, walking and cycling could share the use of this link. If necessary separate road links could be set up for each road based modes. Metro, rail and other (e.g. freight) network links are separately set up when available in a zone, for each applicable distance range (e.g. rail links would not be available in a zone unless the zone is large enough to cover two or more rail stations in one zone, in which case the distance range should be at least as large as the distance between the stations). Such network supply characteristics are crucial in modelling the choices of intrazonal travel modes.

It should be made clear that the traffic volume assigned on the intrazonal network links do not appear on the interzonal networks such as set up in 3.4.1. This has two main implications for analysing the model results. Firstly, the large zone sizes in a strategic transport model implies that the traffic assigned onto the interzonal network can in many cases underestimate the total traffic levels, since in the real world, the intrazonal traffic does appear on the interzonal network. For this reason, the actual traffic volume output from a strategic transport model should be treatd with caution. Where required, it may be possible to estimate the extent of the level of this underestimation (e.g. when observed traffic volumes are available, the difference between the observed traffic volume and the output traffic volume on network links from a well calibrated model can be deemed to be the missing traffic on the interzonal transport network. A further step may be taken to link the changes in intrazonal traffic volume (such as between alternative policy runs) and their implied network loads on the interzonal network, although this can be contigent upon the configurations of the model zones and transport networks. Secondly, the sum of model output of both interzonal and intrazonal traffic by distance range in a well calibrated model can reflect unambiguously the level of traffic generated by nework link type and zone, which can be readily used for impact analysis without further processing. The above means that strategic transport model outputs **(1)** are most useful on network links that have relatively minor intrazonal flows (such as the key infrastructure links on inter-district and intercity corridors, where investment decisions are crucial), and **(2)** can be used to assess the aggregate level of local traffic, but would need additional interpretation if the results are to be used for identifying traffic impacts of a very local nature (such as around a local site of trip generation/attraction).

3.5. Initiatives of policy assessment

The methodological considerations above regarding tectical measures for operationalising the strategic transport model provide important insights into the strengths and limitations of the model. However, the technical, modelling considerations should not override the policy and decision support needs. This section considers the roles that a strategic transport model can and should play in emerging economy cities, especially in areas where there are missing links in decision support regaring the development of urban transport systems and their coordination with land use and economic development.

As reviewed in **Chapter 2**, one of the greatst challenges in model predictions is the ability to foresee the direction and magnitudes of medium to long term changes in emerging economies cities. As a result, the current modelling and policy analytics tend to focuse on the short to medium term technical decisions of incremental network development, which is not always coordinatd with land use and economic growth. This has meant that even in cities that have substantially transformed the urban transport systems, critical bottlenecks and servere congestions remain. For instance, Beijing's metro network in the past twenty years have grown from two line of tens of kms to a extensive network of more than one thousand kms covering both urban and the main suburban areas. However, it has often been the case that as soon as a metro line becomes open, it becomes completely full during the peak hour, and across the city the planned capacities of the metro lines have shown to have 'embarassingly under-estimated the current demand' (BTRC, 2012). This also appears the case for the road network in Beijing, as the average road traffic speeds fall significantly between 2005 and 2010 (BTRC, 2007; 2012).

The key lesson learnt in the transport and urban development of past 20-30 years appears that there has been a missing link in transport infrastructure planning which is a robust analysis of the the medium to long term scenarios of transport demand, given the continuing surge in urban population, income levels and consumer profiles.

This medium to long term scenario testing is not merely an act of predict and provide, because investment, regulation, pricing and other forms of demand management can all be factored into the poicy measures of the scenarios.

However, one important consideration in urban transport provision is that residents in a large city tends to expect that the speeds of travel in the most congested parts of the city not to fall beyond a certain level. If the congestion worsens further, the public's perception of ‘unacceptable’ congestion would spur investment and demand management, as well as spontaneous readjustments in the locations of jobs, residents and travel patterns.

For instance, the peak hour average road speeds of central London which has been a congestion hot spot since the Industrial Revolution has remained to stable to the speeds of horse-drawn carriages from the 18th century to this day (at around 17 km/hr), and the average journy times of the London residents have remained stable to around 40-45 minutes per trip since the records began in the National Travel Survey since the late 1980s. In central Beijing, the average speeds have similarly remained stable (to around 15 km/hr) for around two decades since the 1990s before deteriorating in the past few years, and the average journey times of Beijing residents have remained stable between 41-43 minutes/trip since 2000 before worsening to 48 minutes/trip in 2010.

From the literature review in **Chapter 2** it is clear that the strategic transport model alone cannot adequately provide robust predictions of medium jobs and residential location predictions, if they follow the standard implementation such as the MEPLAN implementation in London and the South East of England where the job and housing locations are treated largely as an exogenous input to the scenarios. Whilst such inputs can be provided in England from the land use planning process, a similar set of inputs are not available in Beijing for medium to long term planning (e.g. with a horizon of 2030).nAmong the emerging economy cities, Beijing is relatively well endowed with planning, transport and analytical resources. This means that our modelling methodology would require a practical way to obtain good predictions of future jobs and household locations, if stratgic transport analysis is to achieve its objective of the robust scenario tests.

There are broadly two alternatives for obtaining jobs and households location predictions for testing the transport scenarios. The first is to extend the land use and economic compoents of the strategic transport model to include jobs and household location predictions. The second is to interface for such inputs with a spatial economic and land use model that has strong economic and behavioural underpinnings. There are no definitive answer one way or the other, although given the objectives to develop the strategic transport model quickly and transparently, it would be prefereable to opt for the second alternative where possible. Given that such a spatial economic and land use model has been developed in parallel with this strategic transport model, our approach is to interface with that model. However, in other circumstances the first alternative cannot be ruled out a priori.

This means that the articulation of the modular model structure would consist of four components for investigating the main medium to long term scenarios of transport demand. The first component is a spatial economic and land use module produces the predictions of jobs and household locations. This is coupled with a simpler, more limited land use activity module, a land use/transport interface module and a strategic transport module as discussed above in this chapter.

The linkage of the modules can be **(1)** based on an iterative process interacting among all modules, or **(2)** if the scenarios are to be based on some peak travel times that are found broadly acceptable by the residents, the spatial economic and land use model can be run for a future scenario with a known set of travel costs and generalised costs.

The first approach is what has been commonely used in conventional assessment, usually with the proposed infrastructure investment projects and associated regulations and pricing measures being input into the model and the model working out what the location patterns and generalised travel costs will be as they reach equilibrium. The generalised travel costs may be higher or lower than in the Base Year, which will not be known untill all the spatial economic, land use and transport modules are run to equilibrium.

The second approach effectively works out the travel demand and the requirements for infrastructure investment, regulation and pricing in the opposite way to conventional assessment practice. It first assumes that the residents in the city would demand a certain level of service from the urban transport system, and work out what the jobs and residents location patterns will be given the changes in city size, income levels, expected lifestyle changes etc. The strategic transport then take the location prdictions to work out what the patterns of travel demand will be and how much pressure different parts of the transport will be under pressure, under different investment, regulation and pricing sceanrios.

Whilst the first approach above is more suitable for investigating incremental and marginal changes in the urban transport system through investment and policy packages, such as the case in well developed transport networks under small changes in population growth and socioeconomic profiles, the second approach would seem to be capable of sheding new light onto non-marginal transformations of the economy, demography, lifestyles and travel demand, and thus would help to fill the gap regarding the medium to long term vision for the design of a sustainable transport system for emerging economies cities.

3.6. Summary

This chapter starts with a critical review of the most relevant theories that have been identified in the literature review in **Chapter 2**. It would seem that the real bottlenecks for building practical, policy-informing strategic transport models lie with the need for operational innovations rather than fundamental theories. We therefore address four aspects of operational innovations that become appareent in the discussions. They are the procedures for **(1)** developing, finetuning and validating multimodal transport networks in a quick and efficient manner, given the data difficulties and emerging new sources; **(2)** understanding new data sources, especially vehicle GPS traces and exploiting their potential in identifying traffic patterns in order to gain an in-depth understanding of the nature of congestion; **(3)** estimating congested traffic speeds where they are substantially different from network freeflow speeds, such as during the peak periods, with a comprehensive coverage of the congested areas; **(4)** completing transport network modelling by supplementary intra-zonal transport networks which are of critical importance for land use modelling. Finally, we turn to a strategic overview of the approach to the use of strategic transport models in addressing current needs, particularly in filling a gap of medium to long term vision for reshaping urban transport systems. We further develop the above operational and strategic aspects in a case study of Beijing.

4. Strategic Transport Model for the Greater Beijing Region

4.1. Overview

This chapter aims to test the methodology for a new strategic transport model by implementing it for one of the world's largest and fastest growing city regions – the Greater Beijing Region. There are four main reasons for the choice of the case study area.

First, the Greater Beijing Region encounters many of the common challenges across the emerging economies in Asia, Latin America and Africa, such as those related to the surging consumer demand for energy and other natural resources; improved coordination and integration of land use, transport and urban design is expected to play an important role in curbing the rise in overall resource consumption, cutting pollution levels and developing a more environmentally sustainable approach to economic development and social welfare. More specifically, Beijing is a model of land use, transport and urban design for more than 600 cities in China, of which more than 160 have over one million residents; the policy and development initiatives in Beijing are widely emulated across China, which implies a direct policy impact for one fifth of the world's population.

Secondly, the Beijing City Region is undergoing a rapid development phase with an enormous investment programme coupled with many new regulatory initiatives. There is a keen policy interest in better managing land, resources, and travel demand through better coordination and closer integration. The wider public are also deeply concerned with air pollution, housing shortage in job-rich areas and transport access, and are interested in engaging in the policy debate.

Thirdly, there have been a general build-up in data collection and model building with the Urban Modelling research group in the Martin Centre, where the development of a new strategic transport model can be better supported.

Fourthly, the author of this dissertation comes from the Greater Beijing City region, which make it more straightforward to conduct a case study there.

For the three decades since the early 1980s, China's economy has been fast growing which has brought about significant growth in floor-space construction for commerce and housing, and simultaneously it raised the demand for urban travel.

Faced with unprecedented surge in consumer demand, the policy makers have been conscious in promoting sustainable management of land, resources and urban travel demand. The current measures include encouraging a shift from private car to public transport, charging for parking, a rapid expansion of the metro, light rail and BRT systems and many other associated travel demand management measures. In terms of the long-term development initiatives, an integrated development plan of the Greater Beijing Region has been put forward. The Greater Beijing Region in fact consists of three provincial level entities, i.e. the Beijing Municipality, the Tianjin Municipality and Hebei Province. This blueprint is aimed to coordinate the developments of the cities and suburban areas across the whole region. The combined city region covers an area of around 200,000 square kilometres and is currently home to more than seventy million people. Clearly, the challenges are of an unprecedented scale.

There are a number of large city regions in the world, which have pioneered land use and transport coordination, and achieved impressive progress in sustainable land use and transport developments, such as the Greater London and Greater Tokyo regions. In conducting the case study, we draw upon the experience in strategic transport model development as well as in the evolution of the city regions.

In response to the above quandary, the case study is carried out in two stages. This chapter reports the first stage where we develop a new strategic transport model based on the methodology considerations in **Chapter 3**. The next chapter (**Chapter 5**) then applies this model to test a number of alternative policy scenarios for 2030, in line with the policy analysis horizon for the development of local policies, such as the 13th Five Year Plan at the city and regional levels.

4.1.1. Geographical extent of the Greater Beijing Region

The Greater Beijing Region has its core Beijing and Tianjin municipalities, which are flanked by regional capitals in Hebei Province which include Tangshan, Chengde and Qinhuangdao to the east, Zhangjiakou to the northwest, and Cangzhou, Baoding, and Shijiazhuang to the southwest (**Figure 4.1**). Langfang is a fast urbanising city on the expressway and high-speed railway corridors between Beijing and Tianjin. All the main cities play crucial roles in the city region (Wu, 2001). The vertical and horizontal integration of modern businesses in the region together with fast improving intercity transport links and suburban housing development have started to articulate new interregional connections which are expected to shape the city region into one of the world's largest in the next few decades. Large, forthcoming infrastructure investments such as the new international airport that is being built on Beijing's southern border (National Development and Reform Commission, 2014) with Hebei and the winning of the joint bid of Beijing-Zhangjiakou for 2022 Winter Olympic Games (Xinhua net, 2015) are expected to provide further impetus to the regional integration.

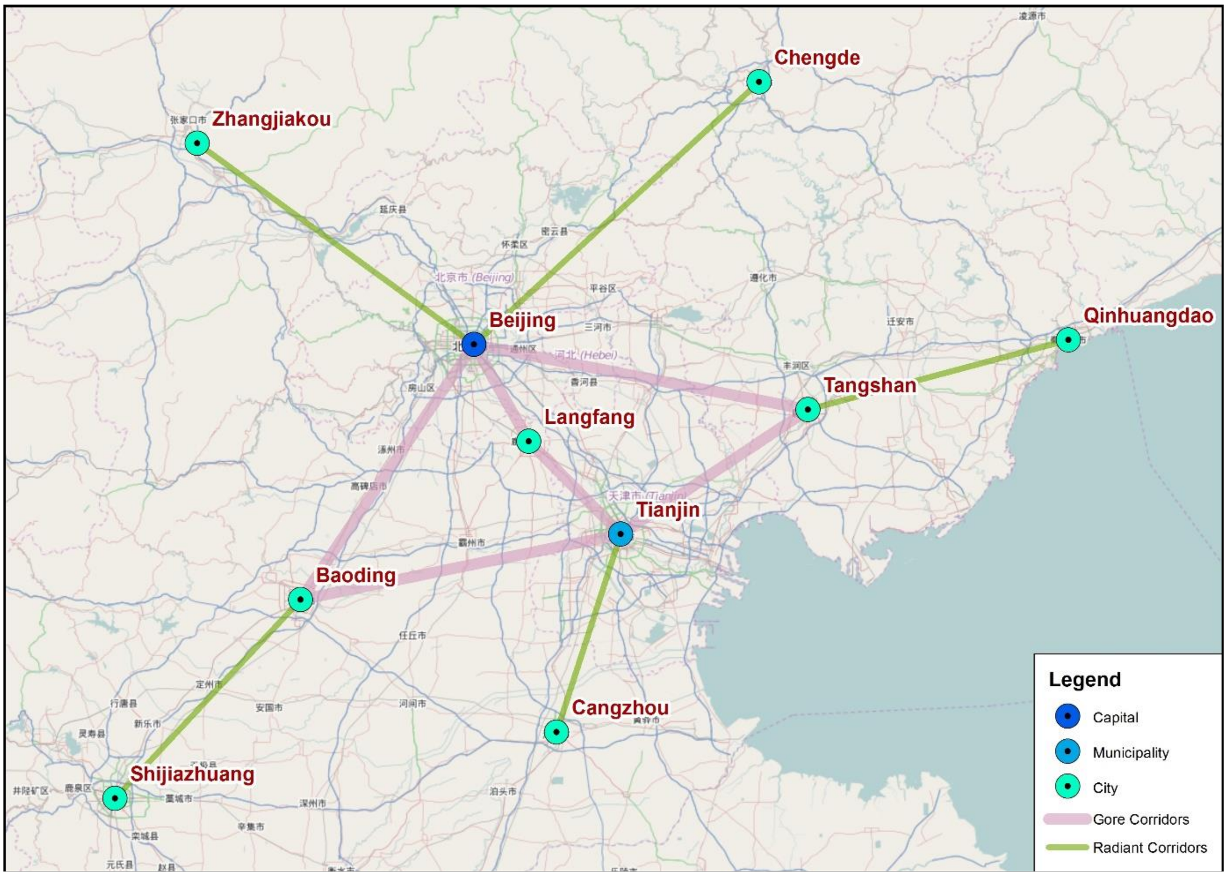


Figure 4.1. Main regional hubs in the Greater Beijing City Region

As seen, the region covers more than 10,710 square kilometres (1% of China's total land territory) with 110 million residents (2014). Due to the development of the expressway and the high-speed-railway networks, the travel time between Beijing and these cities have been cut to one hour or less, which is expected to accelerate economic integration through making daily commuting possible between those cities. However, in the foreseeable future the built-up areas of Beijing is still expected to dominate the city region in terms of population size, density and urban transport challenges (**Figure 4.2**) as well as the availability of good quality land use and transport data. For this reason, it is advisable to start the development of the strategic transport model with a focus on the Beijing municipality. This consideration is implemented in the model specifications as detailed below.

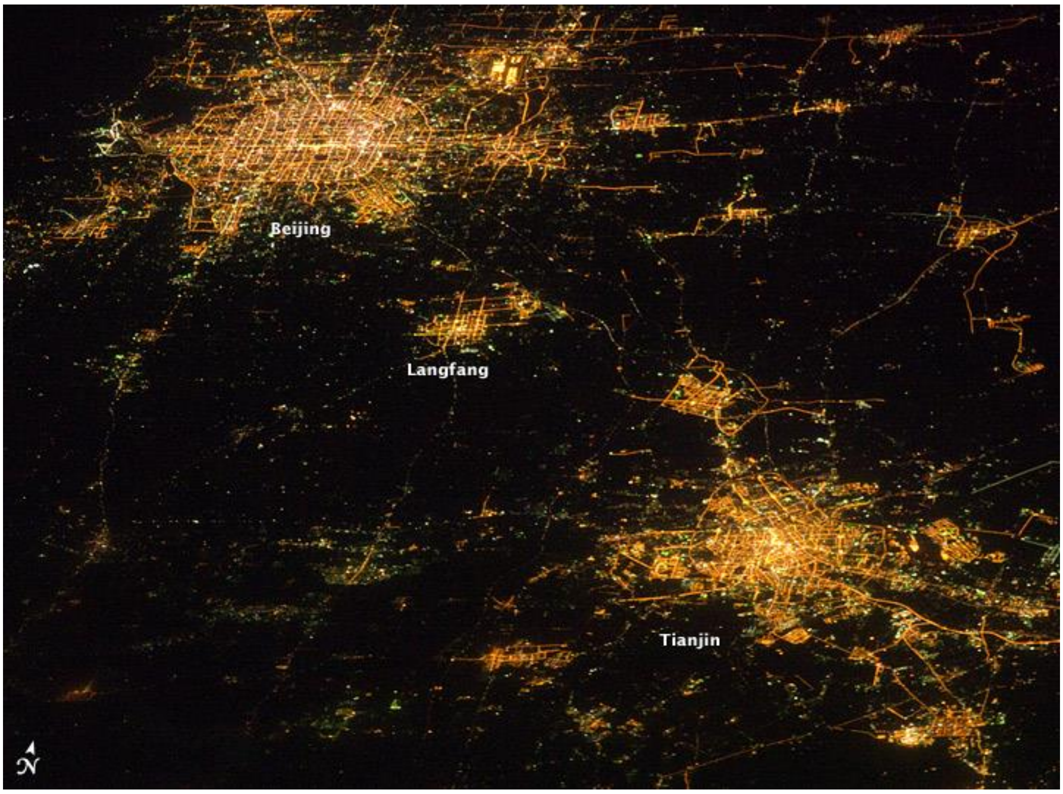


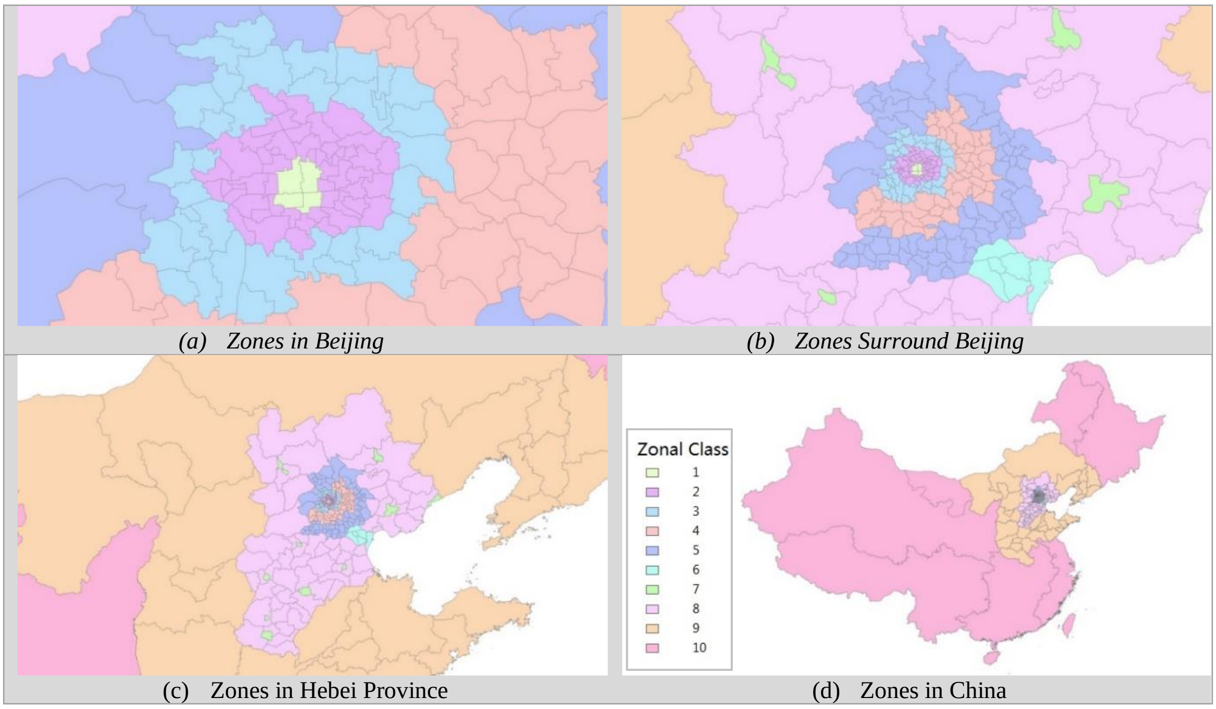
Figure 4.2. A Nightlight Satellite Photo of the Core Greater Beijing Region
<Source: NASA, 2010>

4.1.2. Zoning System and Other General Specifications

From the literature review in **Chapter 2** and methodological development in **Chapter 3**, it is clear that the number of model zones and other model dimensions in general should be kept relatively low. This lessens the data hungriness of the model, and allows the model outputs to be thoroughly checked. Also, it is not clear whether a high number of model zones would directly contribute to a high quality of the model, so long as the model design is well informed by the understanding of micro-scale behaviour mechanisms. With this consideration in mind, we have started out designing the zoning system with a total zone number of 200-300 that is similar to an established strategic land use and transport model in the UK of a similar land area and total population size (Williams, 1994; Jin and Williams, 2002). After several rounds of zoning design and refinement, we have settled down to 221 model zones for both the land use and the transport model. This covers the entire Greater Beijing City Region, (i.e. Beijing, Tianjin, and Hebei), plus the external zones which cover the rest of China. The 221 zones are categorised into 10 different classes due to their geographical location, as shown in **Table 4.1**.

Table 4.1. Traffic Zone Classification

Classification	Description	Spatial extension level
1	Central Beijing	Census Neighbourhood
2	Other Beijing urban districts	Census Neighbourhood
3	Beijing suburban districts	Census Neighbourhood
4	Suburban areas to the Southeast of Beijing	Census Neighbourhood
5	Rural hinterland around Beijing	Census Neighbourhood
6	Tianjin Municipality	Urban District
7	Major cities in Hebei province	Urban city
8	Other areas in Hebei province	Urban District
9	External regions surrounding Hebei province	Sub-province regions
10	External regions in other parts of China	Province or group of provinces



(a) Zones in Beijing

(b) Zones Surround Beijing

(c) Zones in Hebei Province

(d) Zones in China

Figure 4.3. Definition of model zones

As seen in **Figure 4.3**, even though the case study area is focused on Beijing and its immediate surrounds, the model zoning system covers entire China. This is to facilitate the modelling of all relevant transport flows including all those within the Greater Beijing Region and between it and the rest of China. The spatial boundaries of model zones are derived through considerations of the administrative boundaries as defined by China National statistics, the land use characteristics, transport access, and the land use planning strategies in the Greater Beijing Region (Zhao, 2010).

Among the model zones, there are 130 zones for the area within Beijing Municipality, which are defined as single or multiple pre-2010 local administrative Jiedao areas (i.e. Census Neighbourhoods which are a sub urban district administrative unit, see Appendix 1). They are the most detailed zoning, which is in line with the focus of the modelling study. In the immediate surrounding areas outside Beijing, the zones are kept relatively small, usually at the county or urban district level, particularly in areas where there have been plans to expand housing and transport capacities to lessen the development pressures of central Beijing. Other parts of the Greater Beijing Region are zoned at two levels: within the Tianjin municipality, the zones are at a relatively detailed urban district level in order to differentiate travel accessibilities to Beijing (e.g. by high speed trains). For the rest of the areas in Hebei, the major cities are separated from their rural hinterland. The rest of China is divided into zones at province or group of province level.

In addition, key airports, railway stations, prominent special business zones are also defined as model zones.

4.1.3. Modelling framework

As discussed in **Section 3.2.3**, the land use and transport models run interactively through time to assess the longer term effects of policy interventions (e.g. **Figure 3.3**).

As a starting point, the **Calibration Year** of the Greater Beijing model is 2010. The model is run in the 'base' mode in 2010, and its parameters are finetuned to the best available observed data sets that we have been able to collect. This is trailed by a **Validation Year** of 2000, where the model is run in the 'predictive' mode and assessed against the local survey. It is worth noting that due to the availability of local survey, the model adopts a Validation Year (2000) that a decade earlier than the base Calibration Year. Subsequently in **Future Year 1** of 2020 and **Future Year 2** of 2030, the model runs with inter-temporal average costs and interim land use decisions, allowing the assessment of longer-term effects of different policy and operational interventions respectively till 2020 and 2030.

4.1.4. Other general model specifications

The basic units of measurements in the model are defined as: cost in Fen (one cent of Yuan in 2010 prices), time in minutes, and capacity (for a 3 hour AM peak period) in passenger car units (pcu's) on road, and passengers on rail. For this dissertation, the strategic transport model is limited to the AM peak modelling only, covering 3 hours of traffic from 6:30 to 9:30AM on a typical working weekday which is compatible with the main travel surveys in Beijing (see BTRC, 2007; 2012).

4.1.5. Development of modelled transport networks

A central part of the model specification is the building of transport networks. For building the Base Year transport networks, we start from the more recent year (i.e. 2010) as the data for this year is more easily obtainable than that of 2000. We collect information about key transport projects that had been completed between 2001 and 2010 (Beijing Transportation Research Centre, 2005), and thus deduce an approximate transport network for 2000 by subtracting the developments implemented 2001-2010. We further collect information regarding the planned developments of the transport network from government agencies which is used to build the future year networks for 2020 and 2030.

4.2. Base Year Transport Network for 2010

As a key task of the research, a series of complex GIS networks, across all major modes, including urban road, expressway, metro, railways and high-speed railways have been developed to represent all traversable links for passenger travel within the case study area. Since the networks are also used for implementing GPS-based analyses, the road networks need to be suitably detailed to facilitate the mapping of vehicular GPS signals along urban road or expressway links. This means that in Beijing City (within the coverage of the source GPS data), the network data must include detailed representation of multi-lane and multi-directional network links, including those at complex junctions and complex road alignments.

Network data at such a fine granularity is not publicly available in Beijing. Even there are openly accessible data sets, such as OpenStreetMap (OSM) and online map layers (e.g. Google or Baidu), they cannot be used directly for the strategic transport model, mainly due to that **(1)** they are not stemmed from the transport modelling purpose, and may have some topological glitches, such as wrong link direction or misconnection between link and junction node; **(2)** the data for public transport networks, such as metro lines or railways, is not detailed enough, requiring supplementary information from respective transit operators; and **(3)** there is no data found for the connectors between different modal networks.

Therefore, to establish a representative transport network for this study, we need to follow the steps that introduced in **Section 3.4.1**, including:

(1) Draw up different modal network layers based on open-source base map data;
(2) Verify the technical specification of each network layer, including their connectivity and topology;
(3) Define the characteristics of each network layer, such as the key features of network links, including capacity, length, free-flow speed etc; and
(4) Create connector links between different network layers, making all layers connected and accessible to each other.

4.2.1. Network creation

4.2.1.1. Sketching initial networks

We take the OpenStreetMap (OSM) data for 2013 (OpenStreetMap website, 2011) as a starting point, which tends to provide the information that can support such details. Based on the OSM shapefiles for links and nodes, we manually draw up four different layers of network data on the GIS platform (ArcGIS), including:

- **Urban road networks**

To optimise the available time and resources, four different levels of network authenticities are implemented, across from highest-pixel accuracy in the core study area of Beijing City for both transport modelling and GPS analysis, through high-pixel accuracy in Tianjin City and reasonable accuracy in Hebei province, to simplified networks in the periphery of the study area.

In Beijing Municipality, where the urban road network is built with the highest authenticity, the road network links include all major city links, tunnels and bridges, and they retain their geo-coding as defined in the OSM.

With the fourth largest population in China, Tianjin is another provincial-level municipality (under direct administration of the central government) like Beijing. Since the open of China first high speed railway (2008), it takes only half an hour between Tianjin railway station and Beijing South Railway Station. Several expressways also link Beijing and Tianjin within two hours. The traffic interactions between the two metropolises become more and more frequent, and the development of Tianjin has significant impact on the future planning of Beijing. Therefore, even though the case study is focused on Beijing Municipality, the urban road network in Tianjin road is in a comparatively high resolution for modelling accuracy.

The urban road network in Hebei province has a lower level of precision. The road network there covers all major road links, but may miss small local roads. The bridges or tunnels are simplified into road links and the junction nodes are coded as simple cross-roads.

In external area (outside Hebei province), the urban road network is further simplified to represent the transport network. These links are in majority straight lines which link road junctions in Hebei and their nearby junctions outside.

- **National expressway networks**

In addition to the above municipal and provincial road networks, the road connections through the national Expressway Network are also playing a key part in road transport. By the end of year 2014, China has built up the largest national expressway network by length (over 110,000 kilometres) in the world, as shown in **Figure 4.4**.

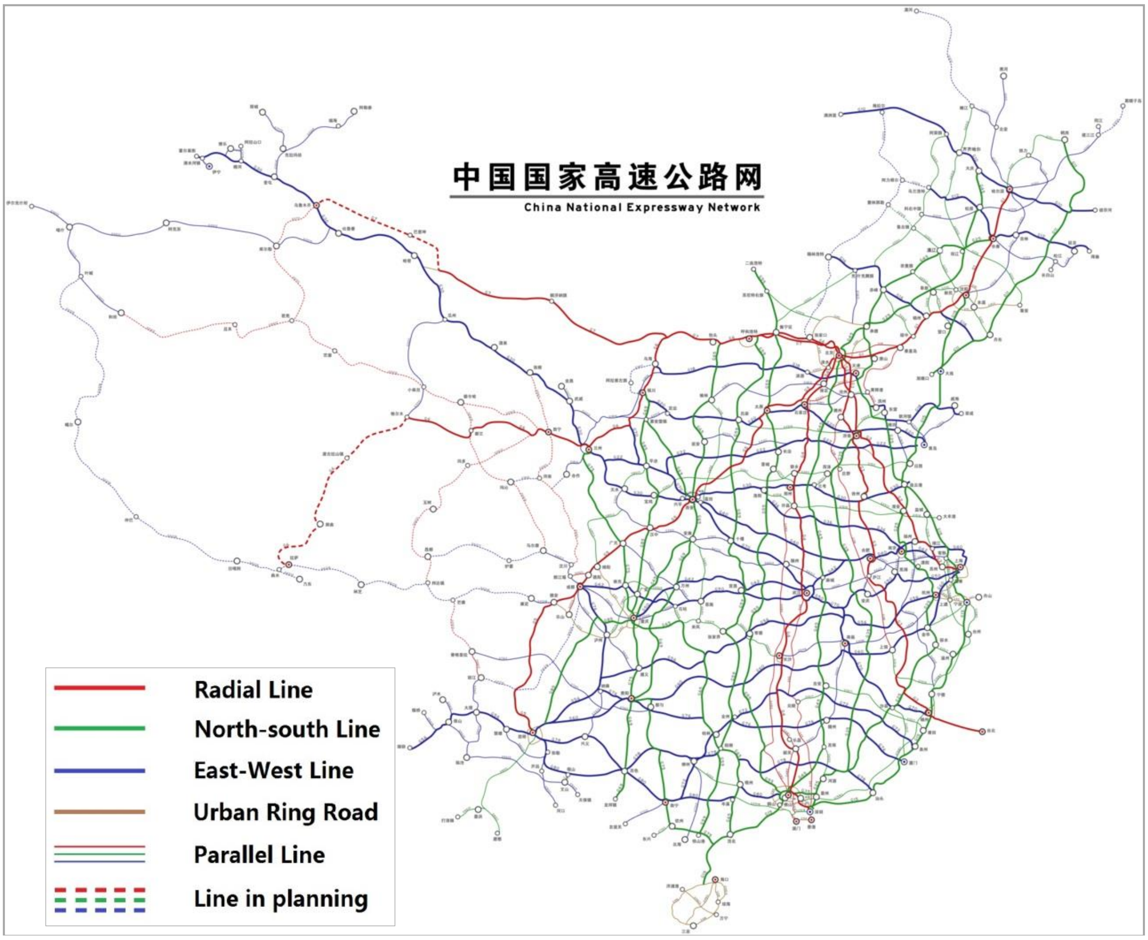


Figure 4.4. China National Expressway Network (2014)
Source: <http://www.chinahighway.com>

Therefore, we have coded the national expressway network based on OSM (2013), which include all the key expressways. The expressway sections that within the Beijing City have fine details, and as farther out, the modelled expressway links morphed into more simplified forms.

- **Urban metro networks**

Both Beijing and Tianjin have their own metro systems (locally known as 'subways'). In this model, we include both the massive metro system in Beijing and the emerging metro grid in Tianjin. The creation of both metro networks is manually based on the OSM (2013), as well as local guides and online maps (e.g. Google and Baidu) for exact locations of metro stations.

- **Rail networks**

Railway plays an important role in the transport system for the Greater Beijing Region. The 2010 railway network in the model consists of both conventional railway links and high speed railway links. High-speed rail (HSR) in China refers to any passenger train services with an average speed of 200kmh or higher. Passenger services below 200kmh are considered conventional services. Both of the ordinary rail network and the high-speed rail network have been built based on the OSM (2013), with adjustment according to the local guides and online maps (Baidu.com).

4.2.1.2. Verifying technical specifications

Through the initial step discussed above, we have established the backbone framework of different layers of modelled network. In the second step, we verify the technical specification of these base frameworks. This involved three major tasks, including:

- **Sense checks**

Several aspects of the primary network layers have been sense checked to ensure that the network is accurate to ensure a robust transport modelling and is also fine-grained to enable the lane-level GPS analysis. These include: **(1)** the accuracy of the geo-coding, e.g. number of lanes and directions of road links; **(2)** the granularity of the road and expressway networks within Beijing City, which should be suitably detailed to accommodate a map-matching method that is able to facilitate the identification of traffic delays and the estimation of network speeds; and **(3)** the topological structure, to eliminate the unexpected conditions that may introduce errors to transport modelling, such as undershoots, overshoots and misconnection on links.

- **Network refinement**

Despite the high accuracy of the manually generated road network, the level of detail (particularly the completeness of its coverage) is not high enough to accommodate the requirements of the proposed map-matching approach. To address this issue, we have developed a geo-processing model to examine the network connectivity and enrich the network with 'infill' links.

In the initial road network building we had included only the main urban roads (i.e. down to the main streets in cities but left out minor streets and unclassified roads in suburban and rural areas. We tried this network with the vehicle GPS data and found that further network details had to be included. As a result, we have here included further details, such as Hutongs (i.e. narrow streets or alleyways in Northern Chinese cities), unclassified suburban and rural road, and some parking accesses. This is done through developing a GIS geo-processing model that **(1)** validates the connectivity of the network and **(2)** generates 'infill' links from the raw Open Street Map database.

The generated 'infill' links are added to the network, in a seamless and topologically valid manner and are classified as 'infill' links. As such the resulting network describes all traversable real-world roads within the fifth ring road and is suitable for the speed estimating exercise that follows.

4.2.1.3. Defining network characteristics

In the third step, we define the relevant characteristics of network links, including capacities, free-flow speeds and charges etc., which are segmented by different link types, and each of the network links has been specified with a sets of characteristics based on their link types. Some network features may also be attached with an "opening year", which plays a key role in the creation of transport networks in other model years.

The definition of link types are based on the information provided by the OSM (2013), while characteristics of free-flow speeds and capacities (including both number of lanes of per-lane capacity) are defined as the construction design values for each different link type (or average of these design values if applicable), road user charges are mainly sourced from local guide and field survey.

- **Urban road networks**

Table 4.2. Modelled urban road links in Beijing (2010)

Type Code	Description	Charge (¥/km)	Free Flow Speed (km/h)	Capacity (pcu/hour)	
				Per lane	One-Direction Total
3200	Beijing 2nd ring road	0	80	1600	5600
3300	Beijing 3rd ring road	0	80	1600	6400
3400	Beijing 4th ring road	0	80	1800	7200
3500	Beijing 5th ring road	0	90	1800	7200
3600	Beijing 6th ring road	0.5	110	1800	7200
3201	1st class road within 2nd ring road	0	80	1800	7200
3301	1st class road between 2nd and 3rd ring road	0	80	1800	7200
3401	1st class road between 3rd and 4th ring road	0	80	1800	7200
3501	1st class road between 4th and 5th ring road	0	80	1800	7200
3601	1st class road between 5 n 6 ring road	0	80	1800	7200
3203	2nd class road within 2nd ring road	0	60	1600	5600
3303	2nd class road between 2nd ring road	0	60	1600	5600
3403	2nd class road between 3rd and 4th ring road	0	60	1600	5600
3503	2nd class road between 4th and 5th ring road	0	60	1600	5600
3603	2nd class road between 5th and 6th ring road	0	60	1600	5600
3205	3rd class road within 2nd Ring	0	50	1200	4500
3305	3rd class road between 2nd and 3rd Ring	0	50	1200	4500
3405	3rd class road between 3rd and 4th Ring	0	50	1200	4500
3505	3rd class road between 4th and 5th Ring	0	50	1200	4500
3605	3rd class road between 5th and 6th Ring	0	50	1200	4500
3207	4th class road within 2nd Ring	0	40	1000	3000
3307	4th class road between 2nd and 3rd Ring	0	40	1000	3000
3407	4th class road between 3rd and 4th Ring	0	40	1000	3000
3507	4th class road between 4th and 5th Ring	0	40	1000	3000
3607	4th class road between 5th and 6th Ring	0	40	1000	3000

Note: <road capacity is estimated as number of lanes multiplies the per-lane capacity>

Urban road links in Beijing are classified into 25 different types based on design speed, capacity and location in the road network, as shown in **Table 4.2**.

In external area, including Tianjin City and Hebei Province, road networks' characteristics are less specific with ball-park definitions based on their overall construction standard as shown in **Table 4.3**.

Table 4.3. Modelled urban road links in external area (2010)

Code	Description	Charge (¥/km)	Capacity (CPU/hour per lane)
5002	First level city major links	0	1800
5003	Second level city major	0	1400
5004	Third level city major	0	1200
5005	Fourth level city major	0	1000

The road network in Hebei province has a lower level of precision. The road network there covers all major road links, but may miss small local roads, as shown in **Figure 4.8**. The bridges or tunnels are simplified into road links and the junction nodes are coded as simple cross-roads.

Besides the above characteristics, link lengths are calculated based on road network distances, which would support the calculation of reasonably accurate distance, costs and average travel times for traffic to and from the Greater Beijing Region.

- **National expressway networks**

Table 4.4. Modelled expressway links (2010)

Code	Description	Opening Year	Charge (¥/km)	Free Flow Speed (km/h)	Capacity (pcu/hour total one direction)
1001	Jing Ha (G1)	2000	0.5	120	8000
1002	Jing Hu (G2)	1993	0.34	110 (90 in Beijing)	8000
1004	Jing Shi (G4)	1994	0.33	100 (80 in Beijing)	6000
1006	Jing Zang (G6)	2001	0.5	100 (60 in rural area)	6000
1012	Beijing Airport (S12)	1993	0.5	120	8000
1028	Beijing Airport North Line (S28)	2006	0.5	120	8000
1030	Jing Jin (S30)	2008	0.5	120 (100 in Beijing)	8000
1032	Jing Ping (S32)	2008	10/car	100 (80 in rural area)	6000
1051	Airport 2nd Expressway (S51)	2008	10/car	100	8000
1101	Jing Jin (S1)	2003	0.5	120	8000
1102	Jing Tong (G102)	1995	0.5	100 (80 in Beijing)	8000
1106	Jing Kai (G106, part of G45)	2006	0.5	120 (80 in Beijing)	8000
1111	Jing Cheng (S11, part of G45)	2009	0.5	100	6000

Since the national expressways in Beijing play an important role in urban road access, and they are subject to different tolling and traffic management operations, we code the expressways with individual link-types. For simplicity, other national expressways outside Beijing are coded as one link type (5001) in the model. The attributes of each Beijing expressway are defined in accordance with its own design and management features, as shown in **Table 4.4**.

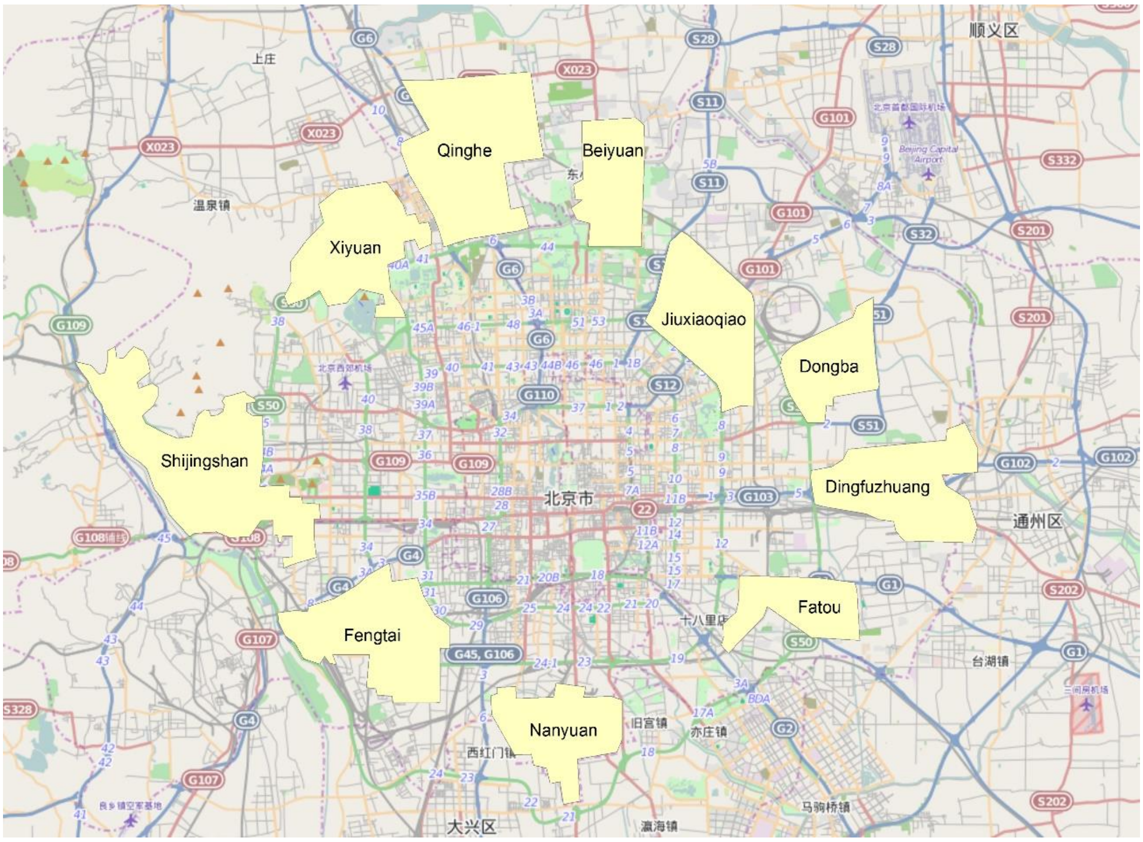


Figure 4.5. Ten Edge Groups around Beijing
<Source: Map created (ArcGIS) based on information from http://www.dili360.com/>

It is worth noting that between the two model years 2000 and 2010, the expressway network in Beijing has experienced significant development, bridging the distant gap between the central area and fringe areas (such as the Ten Edge Groups as shown in **Figure 4.5**). In the strategic transport model, we reflect this profound change from several aspects as follows:

(1) The accessibility to other cities and nearby rural regions has been significantly improved. Four new expressways have been opened, including the Jing-Jin expressway (type code 1030), Jing-Hu expressway (type code 1002) within Beijing (China National Highway 104), Jing-Cheng Expressway (type code 1111) within Beijing, and Jing-Ping Expressway (type code 1032).

(2) The travel time between central Beijing and the Capital International Airport has been shortened dramatically. Three new expressways and one expressway connector line have been completed, including the Capital Airport North Expressway (type code 1028), the Airport Second Expressway (type code1051), the Capital Airport South Expressway (later merged into Jing Ping Expressway, type code 1032), and the Li Tian Road (connector line between the Sixth Ring Road and the Airport Expressway). These expressways reduce travel time between Beijing Fifth Ring Road and the Capital Airport's Terminal Three (which is the main terminal) to less than twenty minutes.

(3) The connections between central Beijing and the rapidly expanding cities in the east and southeast has been strengthened. The Da Guang Expressway has opened in 2009, which links the relatively rural Miyun to Beijing, while several other lines have been upgraded and improved towards new cities, such as Shunyi in the northeast (Jing Ping Expressway) and Tongzhou to due east (Tong Yan Expressway, former Jing Ha Expressway, type code 1001).

(4) The traffic condition into the west, northwest and north Beijing has been improved. The Sixth Ring Road has been completed, and connected to several radial National Highways, such as the newly updated National Highway 108, 109, 110 and Li Tang Road (Central Beijing to Xiao Tang Shan).

(5) The network in rural Beijing has been upgraded. There are a few Class One highways constructed or upgraded, including Baima Road, Mixing Road, Changzhou Road, Shayang Road, Jingtang Road, Yangyan Road, Shunmi Road, Zhouzhang Road, Changhan Road, Jingliang Road, Nanyan Road, Yanliu Road etc.

These key expressways are all modelled with an "opening year" feature in the model, and this will be used to distinguish the network in 2000 from 2010: expressways opened since 2000 onwards are not included in the 2000 model (details are discussed in **Section 4.2.2.5**).

- **Urban metro networks**

Characteristics of modelled metro lines in 2010 in Beijing are summarised in **Table 4.5**.

Table 4.5. Modelled metro lines in Beijing (2010)

Link Type	Description	Opening Year	Capacity (people/day)	Design Speed between stations (km/h)	Operation Speed including station stopping (km/h)
6501	Line 1	1971	20000	60	25
6502	Line 2	1987	20000	60	25
6504	Line 4 (Da Xing Line)	2009	15000	80	25
6505	Line 5 (Yi Zhuang Line)	2007	15000	80	25
6508	Line 8	2008	20000	80	25
6510	Line 10	2008 (partial)	30000	80	25
6513	Line 13	2003	10000	45	25
6530	Airport line	2008	20000	60	25

In Tianjin, there are fewer metro lines and hence a shorter list in our model (**Table 4.6**).

Table 4.6. Modelled metro lines in Tianjin (2010)

Type	Status in 2010	Description
6601	Opened	Line 1, Central City Metro (M01)
6602	Opened	Line 2, Central City Metro (M02)
6603	Opened	Line 3, Central City Metro (M03)
6609	Opened	Line 9, Central City Metro (M09)
6641	Opened	Tram Line in Binhai New Zone
6699	Opened	Central City to Binhai Tram Line

Since 2003, the metro network in Beijing has been significantly upgraded and expanded. Hence in the model, we consider the following changes in the Beijing metro network between 2000 and 2010:

(1) *28th January 2003*, the east side of **Line 13** was opened and connected to its west end (opened at 28th September 2002). Line 13 is the first over-ground urban railway in Beijing, it is also the first new line since 1987. The line connects North Hai Dian District and North Chao Yang District, via the new Hui Long Guan Residential Area.

(2) *27th December 2003*, the first suburban metro, **Batong Line** was complete. This line extends the Line 1 into the east suburbs, from the Sihui until the Tuqiao.

(3) *7th October 2007*, **Line 5** was opened. This is the first metro line connecting the South Beijing to the Central and North Beijing. The north-south connection runs through Beijing Municipality from Tian Tong Yuan North to the Song Jia Zhuang, via several tourist attractions (such as Tian Tan and Di Tan) and the central business area around Dong Dan to the east of the Forbidden City.

(4) *19th July 2008* was a particularly special day in the history of Beijing Metro System. Three important lines were opened that day, and all have served millions of passengers during the Beijing Olympic Games (August 2008). **Line 8** is the Olympic line, which connects the Forrest Park, the Olympic Green and the Olympic Sports Centre to **Line 10** which opened the same day. Most of Line 10 is under Beijing's Third Ring Road, in time for the Olympic Games. The Airport Express Line was also opened this day as the first light railway in Beijing between the Capital International Airport and Dong Zhi Men in the northeast corner of Central Beijing.

(5) *28th September 2009*, the second north-south line (**Line 4**) was opened. This line has 24 stations, and connecting Tsinghua University, Beijing University, People's University, the centre of Zhong Guan Cun high tech research area, Xi Dan Shopping Centre, the Beijing South Railway Station.

In addition, the Tianjin metro was unavailable by 2000 and hence only included in the 2010 model: **Line 1** was opened in 2006, while other lines were opened during 2012-2014.

- **Rail networks**

The backbone of China national railway network consists of 8 North-South lines and 8 West-East lines. In the model, all major railway links for passengers' transport in the study area are coded in the study area as listed in **Table 4.7**.

Table 4.7. Modelled railway network links (2010)

Description	Route & Main Stations	Type
Jing Hu line	Beijing-Tianjin-Jinan-Xuzhou-Bengbu-Nanjing-Suzhou-Shanghai	6801
Jing Jiu line	Beijing West-Hengshui-Fuyang-Nanchang-Huizhou-Shenzheng	6802
Jing Guang line	Beijing West-Shijiazhuang-Zhengzhou-Wuhan-Changsha-Shaoguan-Guangzhou	6803
Jiao Liu line	Jiaozuo-Liuzhou	6804
Jing Ha line	Beijing-Qinhuangdao-Shanhaiguan-Jinzhou-Shenyang-Changchun-Harbin	6805
Jing Tong line	Beijing North-Luanping-Longhua-Chifeng-Tongliao	6806
Jing Bao line	Beijing North-Shacheng-Zhangjiakou-Datong-Jining South-Huhehaote-Paotou	6811
Jing Yuan line	Beijing South-Yanshan-Zijingguan-Laiyuan-Lingqiu-Pingxingguan-Fanshi-Yuanping	6812
Jing Cheng line	Beijing East-Huairou-Miyun-Xinlong-Yingshouyingzi-Chengde	6813
Jing Qin line	Beijing-Shuangqiao-Sanhe-Yutian-Luanxian-Fengrun-Qinhuangdao	6814
Jin Ji line	Tianjin-Jixian	6815

Since the first high-speed railway service opened between Beijing and Tianjin in August 2008, China has built massive high-speed railway networks (19,370km as of 2014). These fast (over 200kmh) transport services have transformed the business and commuting geography within the Greater Beijing Region. In the 2010 model, seven high-speed railway lines have been included as listed in **Table 4.8**.

Table 4.8. Modelled high speed railway links (2010)

Type	Open Date	Designed Speed (km/h)	Capacity (Passenger/h)	Description
6901	June 2011	310	7500	Beijing-Shanghai
6902	December 2012	310	7500	Beijing-Shijiazhuang-Wuhan
6903	December 2012	380	7500	Harbin-Dalian
6907	April 2009	200	7000	Taiyuan-Shijiazhuang-Jinan-Qingdao
6911	October 2003	250	7000	Qinhuangdao-Shenyang
6914	August 2008	250	7500	Beijing-Tianjin
6919	December 2013	250	7500	Tianjin-Qinhuangdao
6990	/	/	7500	Future Lines (not included in 2010 model)

4.2.1.4. Centroid and intermodal connectors

Access links to/from centroid and transfers between the modal networks reflect the connections that make an integrated multimodal transport network for urban travel. There are 10 various types of access links designed to represent the accesses and transfer connections between different transport networks, as shown in **Table 4.9**.

Table 4.9. Access Link Type

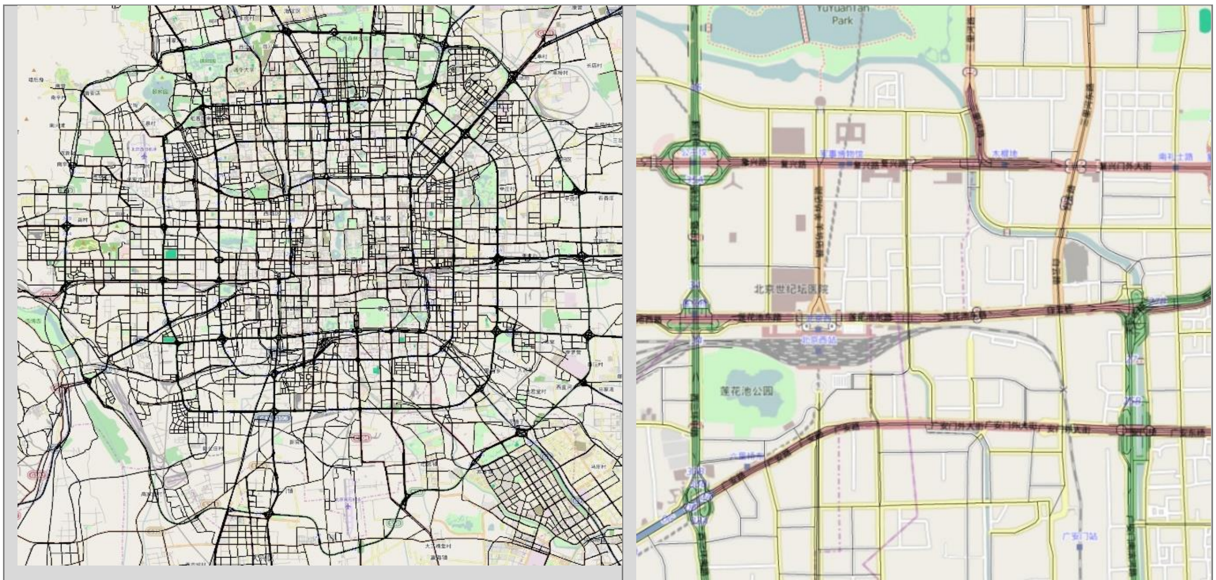
Link Code	Description
8001	Access between zonal centroids to road junctions
8301	Access between railway stations to zonal centroids
8302	Access between railway stations to road junctions
8305	Access between railway station to Beijing metro stations
8306	Access between railway station to Tianjin metro stations
8501	Access between Beijing metro stations to zonal centroids
8502	Access between Beijing metro stations to road junctions
8503	Transfer links between different Beijing metro lines (which locates at the same station)
8601	Access between Tianjin metro stations to road junctions
8602	Transfer links between different Tianjin metro lines (which locates at the same station)

Those accesses and transfer connections are topologically straight lines connecting zonal centroids, road junctions, and metro or railway stations. The accesses between zonal centroids and road junctions or stations (in the same zone with the centroid), can be considered as the unclassified streets or roads within the zone, and help to represent the average local details of accessibility between the building floorspace to the transport facilities in a simplified way. The accesses of railway or metro stations are either exit way or entry way to the nearby road junctions, or transfer links between different metro lines within one same station or between stations nearby.

4.2.2. The resulting network

4.2.2.1. Urban Road Network

As shown in **Figure 4.6**, urban road network in Beijing is fine-grained with infilled links, representing highest-level details and allowing the GPS-based analysis.



(a) Beijing Road Network *(b) Details of Beijing Road Network*

Figure 4.6. Map of modelled Beijing road network (2010)

Although our study is focused on Beijing, but due to the highly frequent traffic interactions between the Beijing and Tianjin, the urban road network in Tianjin City has also been coded with comparatively fine details for modelling accuracy (**Figure 4.7**).

Figure 4.7. Map of modelled Tianjin road network (2010)

The road network in the surrounding Hebei province covers all major road links, but may miss small local roads, as shown in **Figure 4.8**.

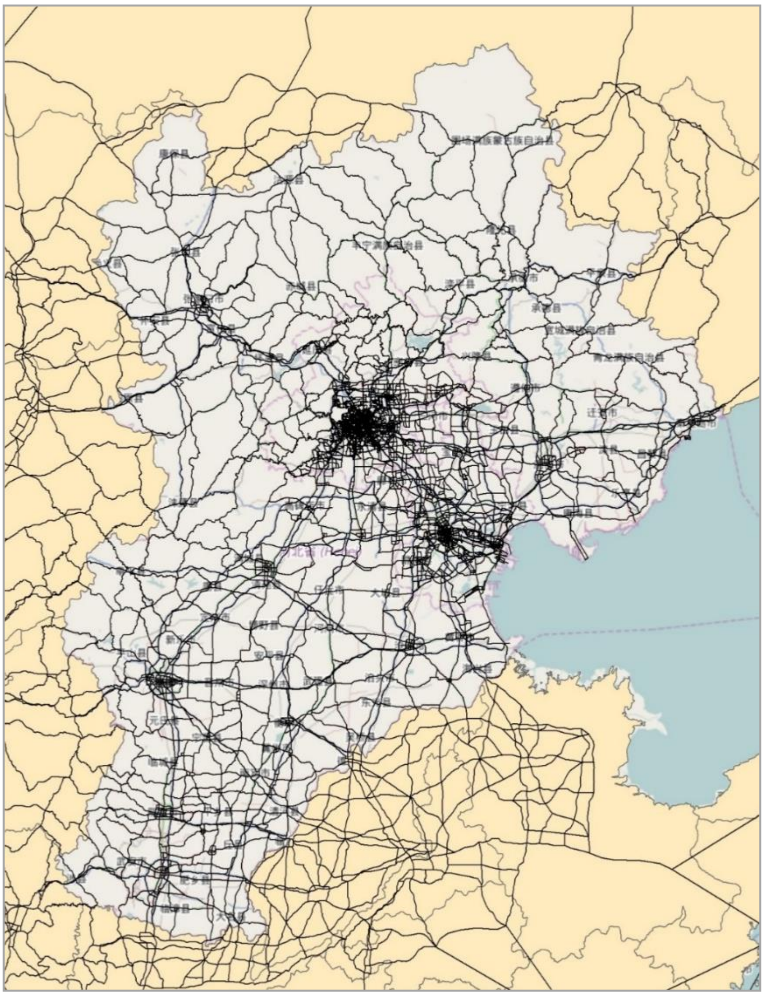


Figure 4.8. Map of modelled Hebei road network (2010)

In the rest of the external area that outside Hebei province, the urban road network has been further simplified to represent the transport network. These links are in majority straight lines which link road junctions in Hebei and their nearby junctions outside.

4.2.2.2. National Expressway Network

As shown in **Figure 4.9**, the model of base year 2010 consists of 14 national expressways which are radial from Beijing.

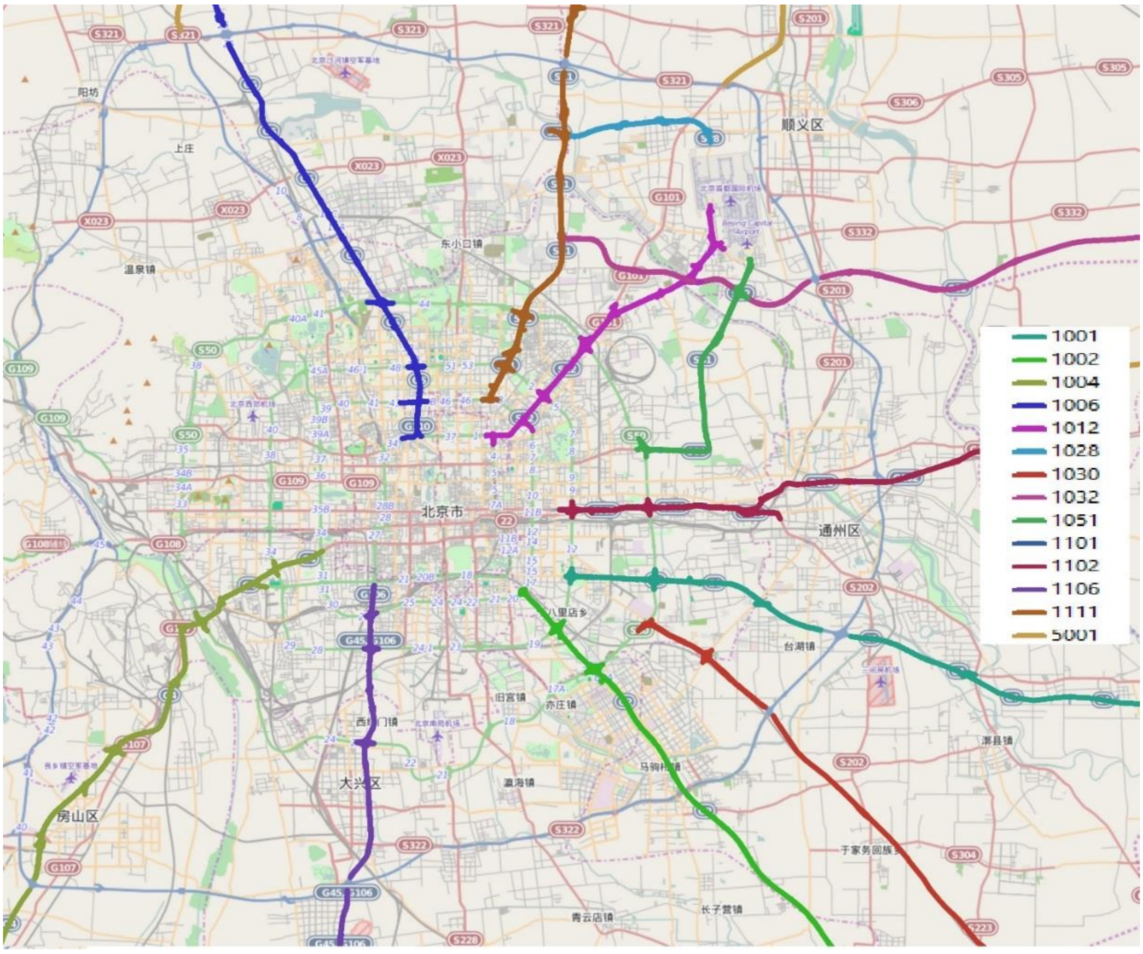


Figure 4.9. Map of modelled expressways network (2010)

4.2.2.3. Urban Metro Networks

The 2010 metro network in Beijing is shown in **Figure 4.10**.

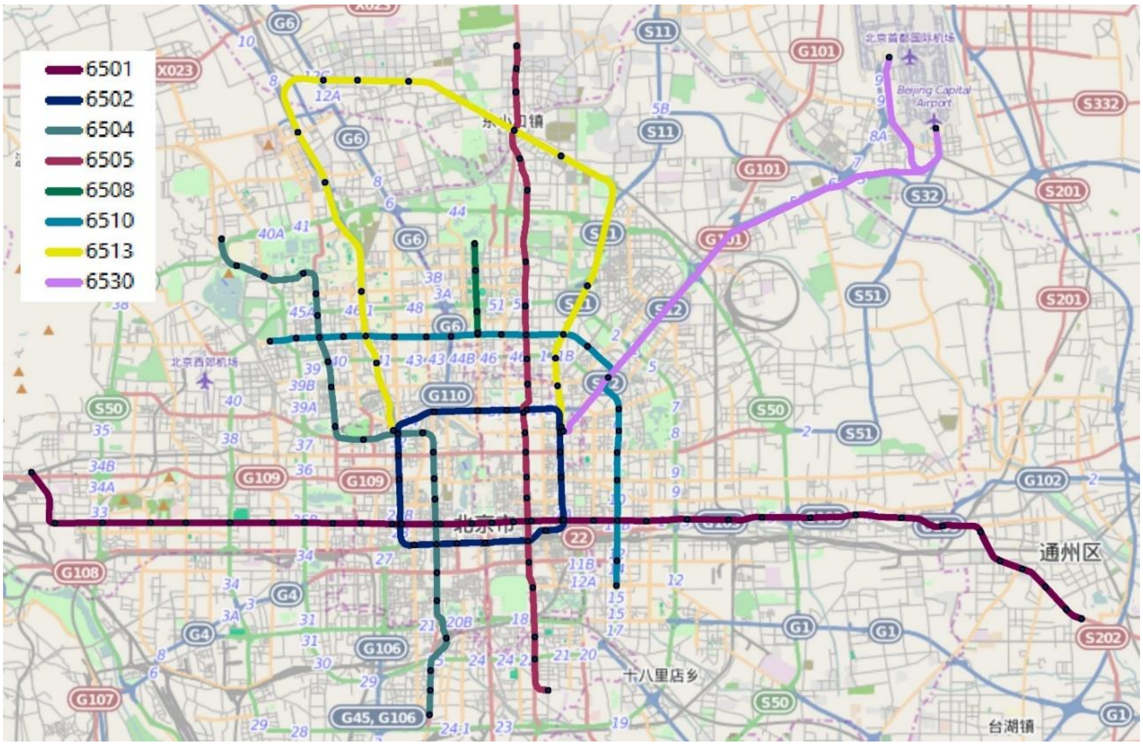


Figure 4.10. Map of Beijing metro network (2010)

The four metro lines in Tianjin are represented in the 2010 model as in **Figure 4.11**.

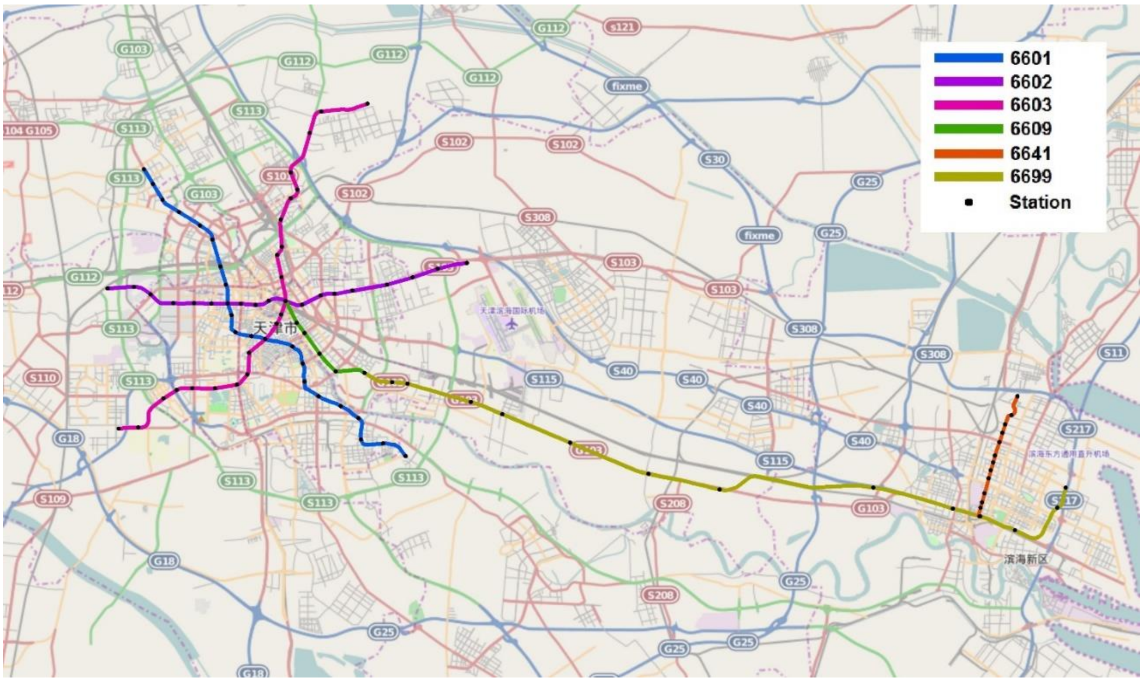


Figure 4.11. Map of Tianjin metro network (2010)

The modelled link types are shown in Figure 4.11.

4.2.2.4. Rail Network

All major conventional railway links for passengers transport in the study area are coded in the 2010 model as shown in **Figure 4.12**.

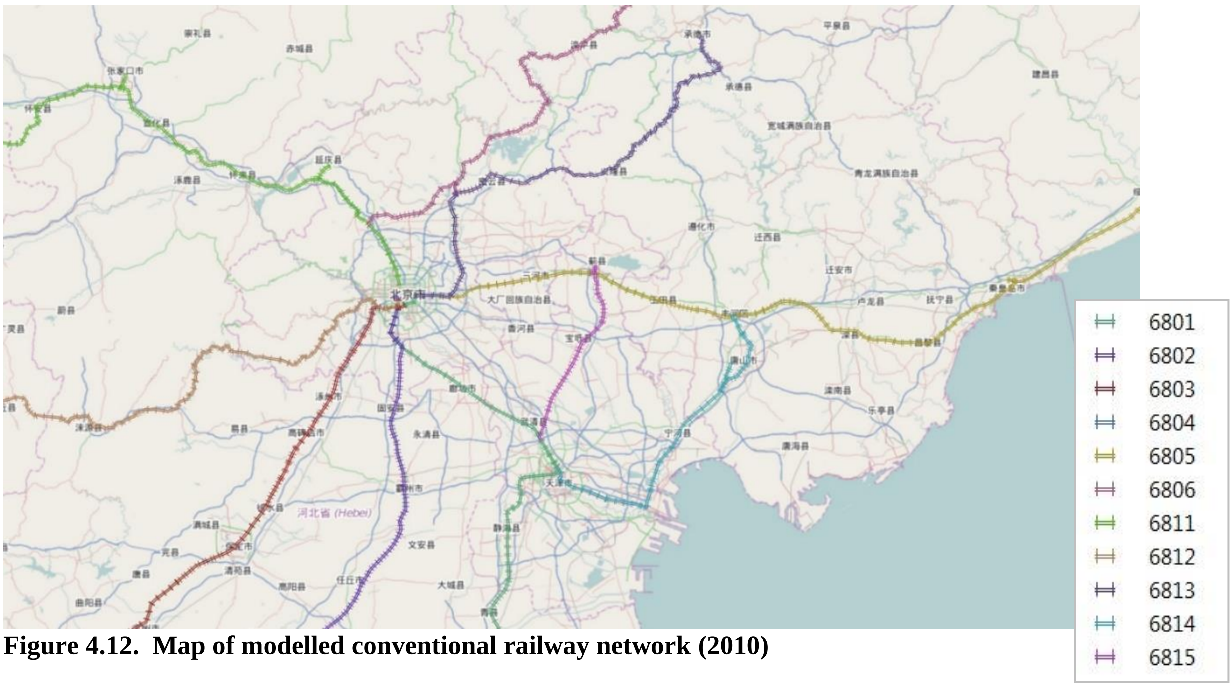


Figure 4.12. Map of modelled conventional railway network (2010)

The seven high-speed railway lines included in the 2010 model are illustrated in solid lines in **Figure 4.13**.

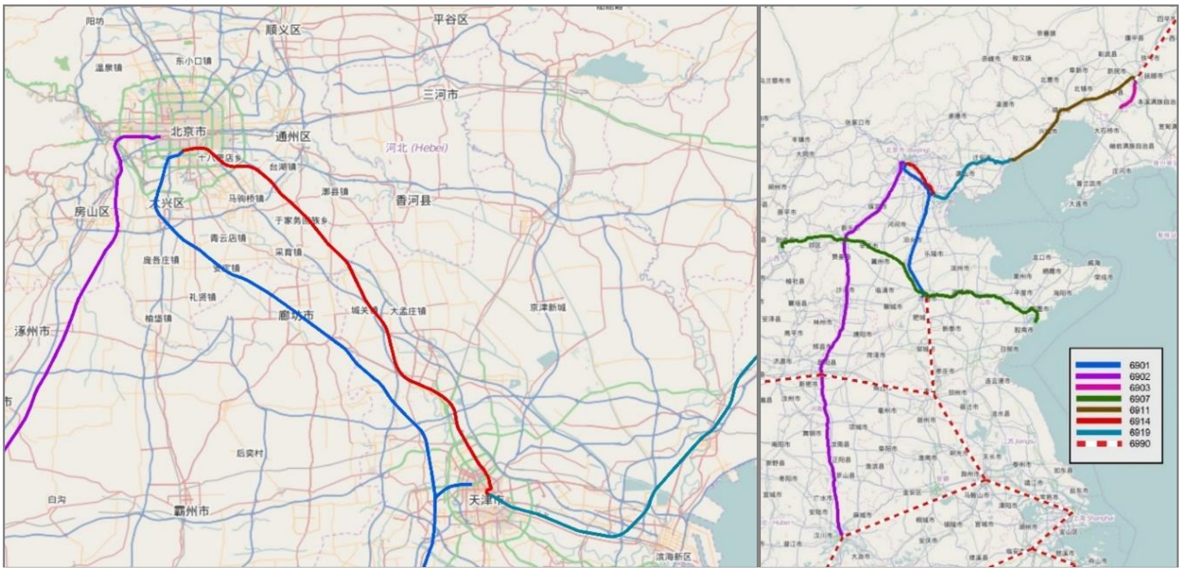


Figure 4.13. Map of modelled high-speed railway network (2010)

4.2.2.5. Intra-zonal Networks

The supplementary intra-zonal transport networks have been developed in accordance with the specifications in **Chapter 3**. Firstly, nine standard distance ranges are defined for road travel (**Table 4.10** below). The number of the distance ranges is specified according to Beijing's Comprehensive Transport Surveys of 2005 and 2010 (BTRC, 2007; 2012). Since the travel speeds on roads in the built up areas are usually significantly different from the more sparely populated suburban and rural roads, two types of distance ranges are defined: i.e. distance ranges within a zone which primarily imply urban travel conditions are separately identified from those which primarily imply rural travel conditions. This separation is defined by zone according to local conditions (See **Appendix 2** for details).

Secondly, the number of distance ranges is defined for each zone. This is done through the ArcGIS interface, where the zone boundaries and the radii of built-up areas and entire zones are measured. The radii are then used to determine how many range links will be needed in each zone for both built-up and rural conditions.

Thirdly, for each distance range, intrazonal network links are set up according to modal availability, as presented in **Table 4.10**. For road based modes, two types of road links are set up (i.e. in and outside built-up area) for cars, buses, walking and cycling, each with its own speeds (for an example of the car and metro/rail speeds, see **Table 4.11**). Metro and rail links are only coded in zones where such services are available.

Table 4.10. Intra-zonal Band

Band No.	Distance			Link type definition				
				Within built-up area		Outside built-up area		Other (typically for very large zones)
	From (≥ km)	To (< km)	Average*	Roads	Metro /tram	Roads	Metro /tram	Rail
1	0.00	1.00	0.334	4001	4031	4011	4051	4071
2	1.00	2.00	1.125	4002	4032	4012	4052	4072
3	2.00	5.00	2.800	4003	4033	4013	4053	4073
4	5.00	10.00	6.375	4004	4034	4014	4054	4074
5	10.00	15.00	11.250	4005	4035	4015	4055	4075
6	15.00	20.00	16.100	4006	4036	4016	4056	4076
7	20.00	25.00	21.150	4007	4037	4017	4057	4077
8	25.00	50.00	36.000	4008	4038	4018	4058	4078
9	50.00	Infinity	75.000	4009	4039	4019	4059	4079

*Note:<*Average distance net of local access km (typically 0.1km at each end)>*

Table 4.11. Link Speeds by Intrazonal Band (km/h)

Band No.	Roads in built-up area	Roads outside built-up area	Metro and rail including waiting and transfer
1	4	4	4
2	8	8	8
3	12	12	12
4	16	16	16
5	20	26	20
6	24	31.2	24
7	28	36.4	28
8	32	41.6	32
9	36	46.8	36

4.3. Transport Networks for the Year 2000

Year 2000 is a calibration year for the spatial economic and land use model, and it is important for that calibration to include reasonably accurate transport supply information. The networks for 2000 are derived based on the 2010 network primarily in the following two ways:

- Through deleting transport links that had been opened during 2001-2010: this applies to most of the new metro lines or new railways (such as high-speed rails).
- Through degrading coded 2010 links: i.e. to keep the topology and connectivity of the networks, so as to remove the network improvements implemented during 2001-2010, e.g. the Beijing Sixth Ring Road, which was opened in 2009, is degraded into unclassified urban road links in the 2000 network to represent the pre-existing low grade rural road connections on or near the Sixth Ring Road alignment.

In order to convert the 2010 network into the 2000 network, the above modifications have been made in both the road links (including urban roads and expressways) and the metro network. The conventional railway links are assumed to be the same since few changes have been made. The HSR links in the 2010 network are all removed. Intrazonal links are assumed to be the same for 2000 as for 2010.

It is worth noting that the features of the Year 2000 network links (e.g. link speed and capability) kept the same as in the Year 2010. Changes are not incorporated mainly because from 2000 to 2010, we assume the journey times between the same OD pairs remain at the same level: on the road network, although the functional capacity has been improved since 2000 through the building of new roads, and expanded capacity of existing roads, the traffic has also increased dramatically, leading to approximately the same speeds as before. This has meant that the car and bus speeds remain similar over the years. On trains and metro lines, the operating speeds have remained as before as more trains are incorporated. The assumptions of overall travel time remaining constant have been accepted by the reviewers of Jin et al (2017) in Transportation Research D.

4.3.1. Road Network

4.3.1.1. Urban Road Network

In the 2000 network, if the urban road links in the 2010 network were not opened yet in 2000, those links were degraded into unclassified links with an average free-flow link speed of 25 kmh. This degrading was applied for instance on one part of the Fifth Ring Road and the Sixth Ring Road etc. (**Figure 4.14**). Urban road links that are not revised retain the same link attributes as the road links of 2010.

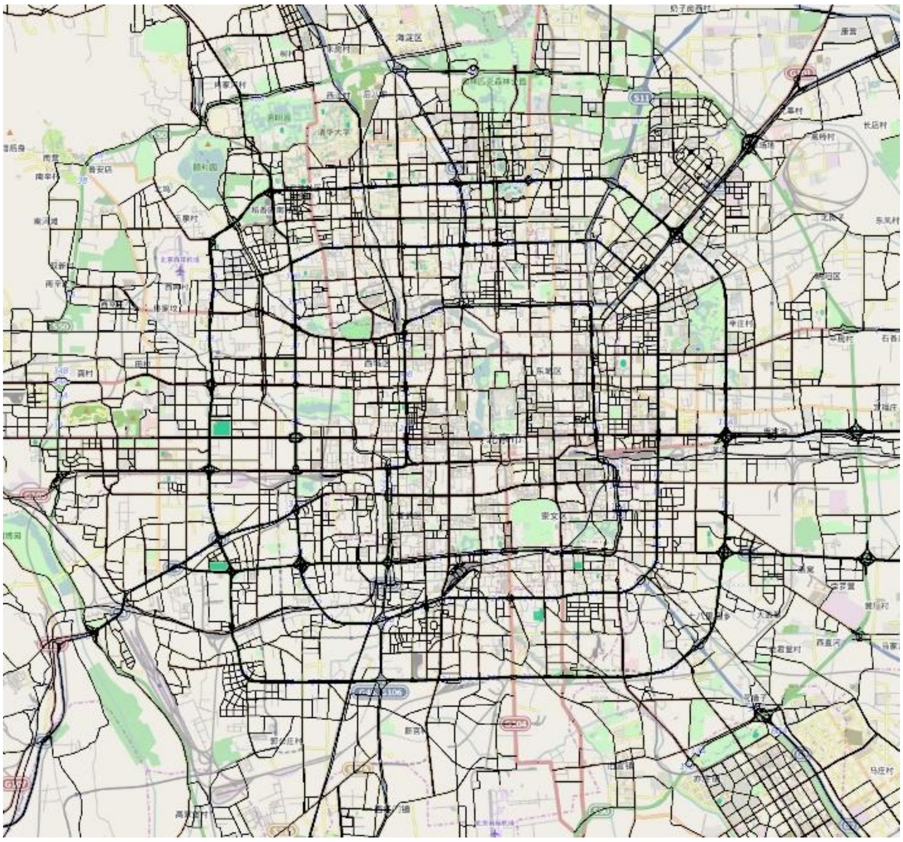


Figure 4.14. Year-2000 modelled road network in Beijing

4.3.1.2. Expressway Network

Like the urban road network processing, the expressways in the 2010 network which did not exist in 2000 are degraded to unclassified road links as well. The retained expressways are shown in **Table 4.12** and **Figure 4.15**, which includes five radial expressways from Beijing and other expressways which we believe had generally been open pre-2000.

Table 4.12. **Modelled expressway links in 2000**

Code	Description	Opening Date	Charge (Yuan/km)	Speed Limit (km/h)	Capacity (car/hour total one direction)
1001	Jing Ha (G1)	2000	0.5	120	8000
1002	Jing Hu (G2)	1993	0.34	110 (90 in Beijing)	8000
1004	Jing Shi (G4)	1994	0.33	100 (80 in Beijing)	6000
1012	Beijing Airport (S12)	1993	0.5	120	8000
1102	Jing Tong (G102)	1995	0.5	100 (80 in Beijing)	8000
5001	Expressway	pre 2000 (Various dates)	0.5	120	8000

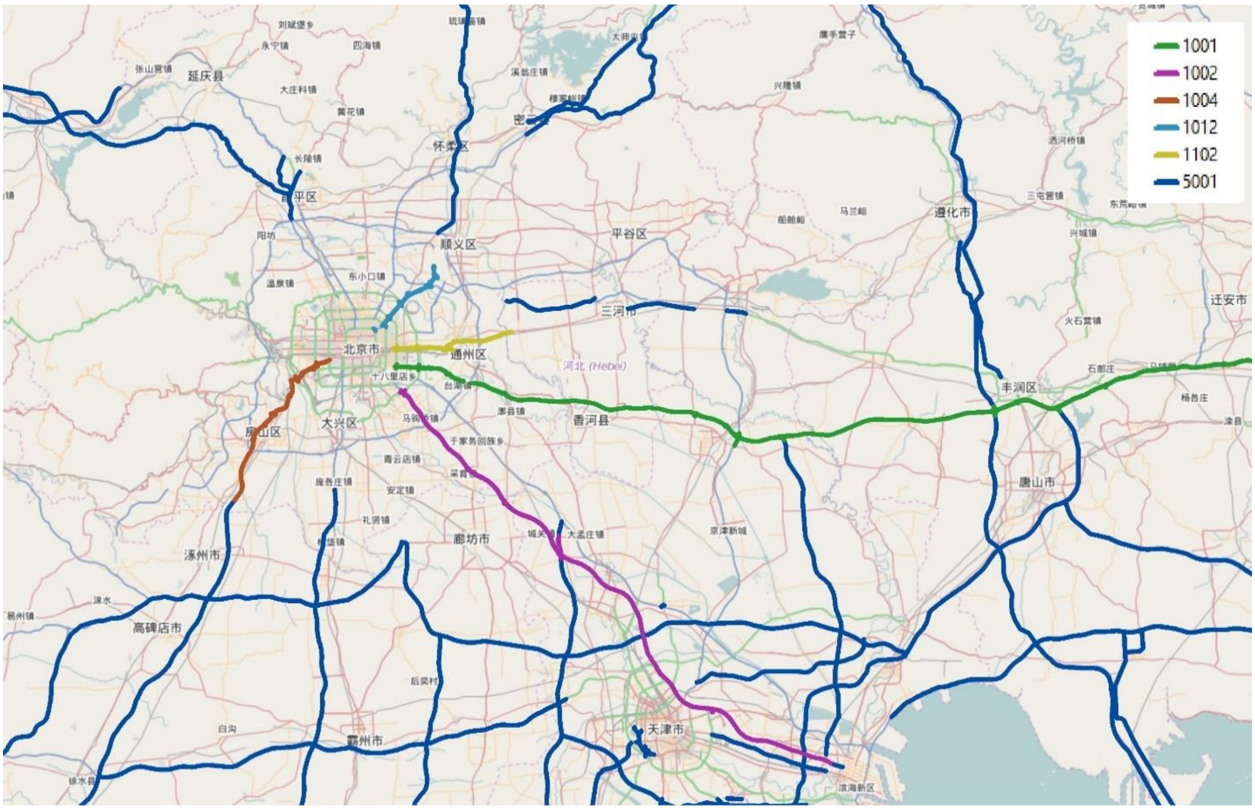


Figure 4.15. Modelled expressway network

4.3.2. Metro Network

Tracing back to 2000, the metro networks in Tianjin and Beijing were both in a very early form of what they are nowadays. During 2001 to 2006, the very limited Tianjin Metro was suspended for reconstruction, so for the 2000 model, no Tianjin metro network links are included in the 2000 network.

While in Beijing, there were only two metro lines serving the citizens at that moment (**Table 4.13**). The first metro line in Beijing, Line 1, is also the first metro in China (1969-1971), with a length of 27.6 kilometres and 19 stations. The other Line 2 (23.03km, 18 stations) was opened subsequently in 1987, although the line's operation was slightly different from that in 2010. These two lines are both retained within the 2000 model, as shown in **Figure 4.16**.

Table 4.13. Modelled link type of Beijing metro network for 2000

Link Type	Description	Opening Year	Capacity (people/day)	Design Speed (km/h)	Operation Speed (km/h)
6501	Line 1	1971	20000	60	25
6502	Line 2	1987	20000	60	25

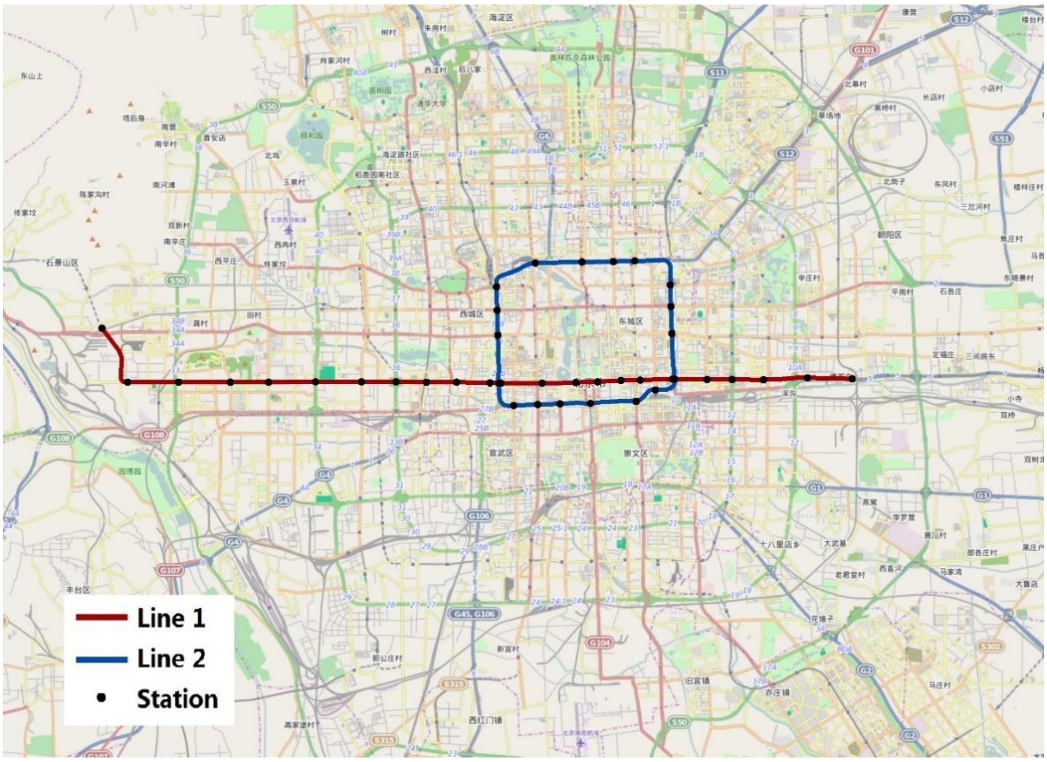


Figure 4.16. Beijing Metro Network (2000)

4.4. Future Year Transport Networks (2020 and 2030)

The strategic transport model in this case study also consists of two future year transport networks in 2020 and 2030 respectively. Based on published government plans, new network links are added onto the 2010 network, which include primarily metro links in Beijing, and also the new high speed railway links in the city region. Owing to the fact that road building and road expansion have started to face severe local popular opposition for environmental concerns across the city region, we assume that the bulk of the urban road network will remain their configuration and specification to 2020 and 2030, and similarly the intrazonal networks will remain the same in terms of link characteristics.

There have been no changes in link characteristics, e.g. congested link speed and capacity, this is because firstly the unavailability of additional data source, and secondly it is likely reasonable to assume that there will have no improvements in speeds in spite of capacity expansions as the demand surges from the growth of income and car ownership in the future years.

4.4.1. Beijing Metro

Since 2010, Beijing has been continuing building up the metro network, which now connects 277 stations (2014) across eleven various suburban and urban districts.

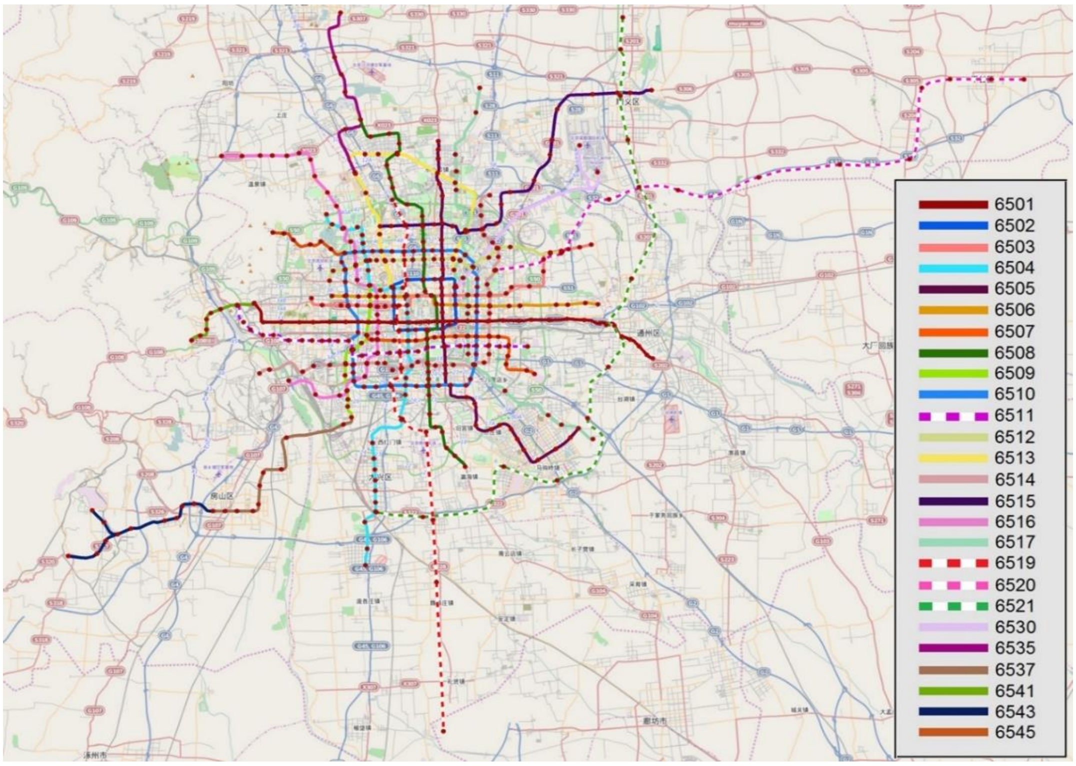


Figure 4.17. Beijing Metro Network in Future Year Model

By December 2014, there were 18 lines (17 metro lines and 1 airport connection light rail) in operation, with a total length of 465km. In the near future, this network is expected to keep expanding up to 1000km by 2020. **Figure 4.17** demonstrates the metro network in future years. The solid lines are included in the 2020 network, and the dashed lines are added to the 2030 network according to the published plans for 2020 and 2030 (Beijing Subway Website).

From 2011 to 2015, the remaining part of Line 8 and Line 10 has been completely finished, and another seven new lines has been built in addition:

(1) *30th December 2010*, four important suburban metro lines were open, including Daxing Line, Changping Line, Yizhuang Line and Fangshan Line. **Daxing Line** extends the Line 4 into the southern suburban region from Gong Yi Xi Qiao station, and runs downwards until Tian Gong Yuan. **Changping Line** was opened partially from the Xi Er Qi to the Jian Tou West. It connects Changping district to Central Beijing, linking several key functional regions, across the emerging Innovation Base, Life Science Park, Science and Technology Park, Shahe Higher Education Park, Shahe Gonghua City etc. The third suburban metro link opened was **Yizhuang Line**, connecting Central Beijing to the Yizhuang Economic and Technological Development Zone. The open of this line will accelerate the development of the southeast Beijing. **Fangshan Line** expands the metro network into the southwest suburb, from the Dabaotai to Suzhuang. This line is later connected to the Guogongzhuang station at 31st December 2011.

(2) *30th December 2012*, the southern part of **Line 9** was open from the National Library in the Haidian District downwards until Fengtai District. In addition to the extension of **Line 8** was partially opened, linking Nan Luo Gu Xiang in Central Beijing to Zhu Xin Zhuang.

(3) *5th May 2013*, the west part of **Line 14** was opened. The Garden Expo station on this line plays an important role in serving the 9th International Garden Expo during 18th May to 18th November 2013. This link also makes it convenience convenient for passengers in Changxindian region of Fengtai District, and accelerates the development of the Fengtai Science and Technology Park. The rest part of **Line 10** was also opened on this date. Thus, Beijing has built up its second metro ring between the Third Ring Road and the Fourth Ring Road - so far it is the longest underground railway in the world, and it proves to be the busiest link in Beijing.

(4) *28th December 2014*, the east part of line 14 was open following its west part. This part of line 14 runs through the CBD and Wangjing residential area, from Shan'gezhuang to Jintai Road. In addition, at the same day, one of the Beijing Metro major backbone lines, the **Line 6** was open (first part of the line has been in use since 30th December 2012). It is an east-west metro line, which is parallel to Line 1.

(5) *28th December 2014*, the eastern part of **Line 15** was open. This line is designed to run across the North Beijing from the Tsinghua East Road until Fengbo station. The eastern part starts from the Wangjing West Station, and stops at the Fengbo station. The rest of the line is still under construction, and expected to be finished by 2020. **Line 7** was also open at this date, and it is one major metro line across South Beijing. This line runs across Fengtai, Xicheng, Dongcheng and Chaoyang Districts, starting from the Beijing West Railway Station to the Jiaohuachang Station.

From 2015 onwards until 2020, another new 8 metro lines are expected to be completed, with the entire Line 7 and Line 14 being open in the near future. These seven new metros are as follows:

(1) **Line 3** is an east-west metro line with 27 stations. This line has already been started to construction, and estimated to be finished by 2018. It is parallel to Line 1 within the Central Beijing, and will help release the traffic pressure of Line 1.

(2) **Line 12** is planned to open in 2020. This line lies between the North Third Ring Road and North Forth Ring Road, with 21 stations.

(3) **Line 16** starts from Wanping in Fengtai District, and pass through Lize Financial Business District and National Library. The opening of this line is expected to accelerate the development of South Beijing.

(4) **Line 17** will be the longest vertical metro line in Beijing in 2019. The line aims to reduce the traffic pressure among the new residential and other emerging functional regions, such as the Tiantongyuan, Wangjin, and the Science and Technology Park etc.

(5) **Mentougou Line**, also known as S1 line, is a maglev railway line with moderate speed and is due to finish by 2016. It will link Central Beijing from Pingguoyuan to the Mentougou district.

(6) **Yanfang Line** is considered as one of the most important measures by the Beijing municipal government, as it will significantly improve the accessibility for the residents in the Fangshan New City, as well drive the development of Yanshan region in the South Beijing. The line is planned to open by the end of 2016.

(7) **Xijiao Line**, also named as Xiangshan Line, is an over-ground tram line being constructed recently, and due to finish by the end of 2016. It will serve the region covering Xiangshan, Botanic Garden, Yuquan Country Garden and the Summer Palace.

In addition, there are four lines (Line 11, 19, 20 and 21) which will be completed around 2030 (As shown in dash lines in **Figure 4.17**).

Table 4.14 summarises all 29 Beijing metro lines in the entire strategic transport model, and specify the metro lines in each year network.

Table 4.14. Summary of Beijing Metro Networks

Link Type	Description	Opening Year	Included in Model			
			00	10	20	30
6501	Line 1	1971	✓	✓	✓	✓
6502	Line 2	1987	✓	✓	✓	✓
6503	Line 3	2018	✗	✗	✓	✓
6504	Line 4 + Da Xing Line	2009	✗	✓	✓	✓
6505	Line 5 + Yi Zhuang Line	2007	✗	✓	✓	✓
6506	Line 6	2012	✗	✗	✓	✓
6507	Line 7	2014	✗	✗	✓	✓
6508	Line 8	2008	✗	✓	✓	✓
6509	Line 9	2012	✗	✗	✓	✓
6510	Line 10	2013	✗	✓	✓	✓
6512	Line 12	2020	✗	✗	✓	✓
6511	Line 11	2030	✗	✗	✗	✓
6512	Line 12	2020	✗	✗	✓	✓
6513	Line 13	2003	✗	✓	✓	✓
6514	Line 14	2015	✗	✗	✓	✓
6515	Line 15	2015	✗	✗	✓	✓
6516	Line 16	2016	✗	✗	✓	✓
6517	Line 17	2020	✗	✗	✓	✓
6519	Line 19	2030	✗	✗	✗	✓
6520	Line 20	2030	✗	✗	✗	✓
6521	Line 21	2030	✗	✗	✗	✓
6530	Airport line	2008	✗	✓	✓	✓
6535	Chang Ping line	2015	✗	✗	✓	✓
6537	Fang Shan line	2015	✗	✗	✓	✓
6541	Men Tou Gou line	2015	✗	✗	✓	✓
6543	Yan Fang line	2015	✗	✗	✓	✓
6545	Xi Jiao line	2015	✗	✗	✓	✓

4.4.2. High Speed Railways

China government has planned to shorten the travel time between Beijing and other major provincial capital cities by implementation further expansions of the high speed railway network.

Figure 4.18. China HSR Network 2025
<Source: www.news.cn>

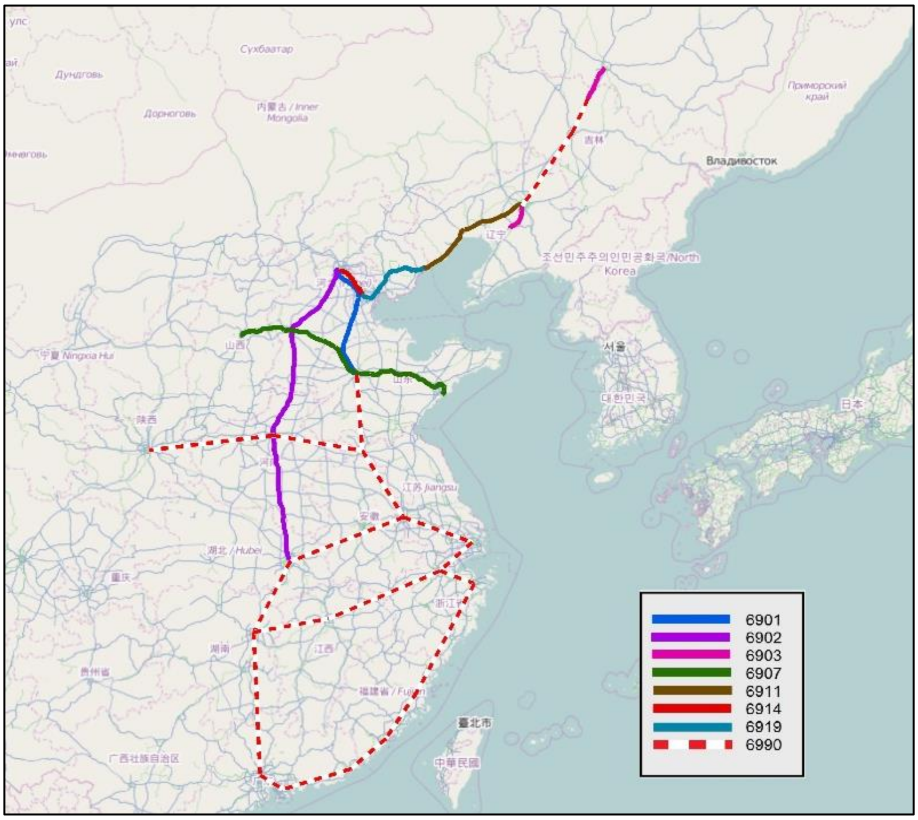


Figure 4.19. High speed railways in future year scenarios

For this case study of the Greater Beijing Region, we consider the new links of the high speed railway network ranging up to the 4-hour (or 4 小时) circle as in **Figure 4.18** the most relevant. We therefore add to the 2010 network a number of new HSR links which are shown as dashed lines in **Figure 4.19**, and they all have the same link type code of 6990.

4.5. Spatial-temporal analyses of Taxi GPS trajectories in Beijing

Although a large number of Beijing taxis have been fitted GPS monitoring devices since the 2000s, there have been very few datasets available of the GPS traces from the operators. One publicly available dataset, a sample T-Drive Data, is that from Microsoft Research Asia (Yuan et al, 2011a, 2011b; Yuan et al, 2010; Zheng, 2011; Zheng and Xie, 2011; Zheng et al, 2009; Zheng et al, 2008）.

This taxi GPS dataset was released for general research purposes (Zheng, 2011). The exact reasons for the choice of the dates (2nd – 8th February 2008) for the data are unknown. However, the dates of the data are remarkably suitable for the purposes of this dissertation for two reasons as follows:

First, the traffic conditions of early 2008 represent what the residents regarded as acceptable for daily activities, as well as what met the approval by the inspections and monitoring by the International Olympic Committee (BOCOG, 2010). In the lead up to the 2008 Games, Beijing's urban travel demand was growing rapidly, and transport infrastructure investment and service operation management were able to respond to this growth. By the end of 2007, roads specified to modern standards in the Beijing had increased from 2,500 kilometres in 2001 to 4,500 kilometres, with expressways totalling 800 kilometres. To tackle traffic congestion, preferential terms were given to developing public transport, with improved public transport facilities, a low-fare policy, increased bus lanes and transit hubs and improved bus route coverage and bus service standards. By the end of 2007, 34.5% of all passengers had used public transport compared with 28% in 2002. In the background, an intelligent city transportation management system was put in place, which integrated traffic command, transportation network management, traffic accident alert system, traffic monitoring, digital traffic policing, expressway control, traffic signs, and real-time traffic assessment. 7,800 environment-friendly taxis replaced old ones and all taxis were equipped with GPS (BOCOG, 2010). In hindsight, early 2008 was a rare time window in the last decade or so when the level of traffic congestion and crowding was found by the residents to be relatively tolerable[2].

Secondly, the three days in the lead up to the Chinese New Year are likely to provide an interesting profile for the transitions from a working day to the eve of a major holiday period. Although it is customary in China to continue working till the Chinese New Year arrives, we would expect to see some transitions in the patterns of traffic as rural migrant workers leave Beijing for their vacations and at least some travellers switch to the preparations of the holidays.

The above considerations regrind the data dates would be immaterial if the continuous monitoring of Beijing taxi trajectories could be made available en masse by the taxi operators or the Beijing transport authorities. There are however few prospects for this to happen in the near future, not only for researchers outside China who are subject to cross-border data control, but also for researchers in China. In this context, we would marvel perhaps the happy coincidence that this dataset of a very substantial number of data points was made available to all researchers. We expect the methods we develop on this dataset will be applicable once more GPS traces become available.

As discussed in **Chapter 3**, there are two types of analyses that our methods can be applied to:

(1) Spatial-temporal analysis of patterns of the slow-moving and stopping taxi traces, which will be discussed in this section. There is little information available about sources and details of the collection of the taxi GPS traces. Hence, to verify that the sample data is capable to reflect the on-road traffic condition in reality (which is required by the strategic transport model development), we apply the DBSCAN clustering algorithm to identify hotspots of the slow-moving and stopping taxi traces.

    Obviously, we are interested in the locations and shapes of slow moving traffic (which we term ‘hotspots’), particularly where batches of slow moving taxis congregate for some reason.[3] Analysis of the patterns of these hotspots will allow examination on the sample

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[2] Over the course of 2008, however, car ownership and car traffic were increasing rapidly with on average 1500 new cars appeared on Beijing’s roads (Huang, 2010), and by October 2008, the traffic conditions experienced in early 2008 could only be maintained through taking one fifth of cars off the public roads within the Fifth Ring Road one day a week. The public responded generally positively to this road space rationing measure as it appeared to maintain the road speeds with no apparent declines until 2012, when traffic congestions and associated air pollution were considered significantly worsened. The concerns then triggered a new measure for constraining the purchase of new cars through a lottery system.

[3] These reasons may involve road congestion, waiting for traffic lights, passenger-related activities (such as picking up or setting down), operational services (such as refuel or repair) etc.

data in comparison of the local guidance and experiences, indicating whether it is appropriate to use the data in the estimation of congested link speeds for the main transport model.

(2) Extracting information regarding congested traffic speeds which we will turn to in the next section.

4.5.1. Beijing Taxi GIS trajectory

The data set (a sample of the T-Drive data[4]) contains about 17.6 million points generated by 10,357 taxis within Beijing between Saturday 2nd and Friday 8th February 2008 (7 days), during which Chinese New Year fell on Thursday 7th February (Zheng, 2011).

It encloses a pile of 10,357 text files. Each file contains all the GPS data points generated by each of the 10,357 taxis over the 7-day period, providing information such as taxi identifier, timestamp (date and time), as well as location in geo coordinates.

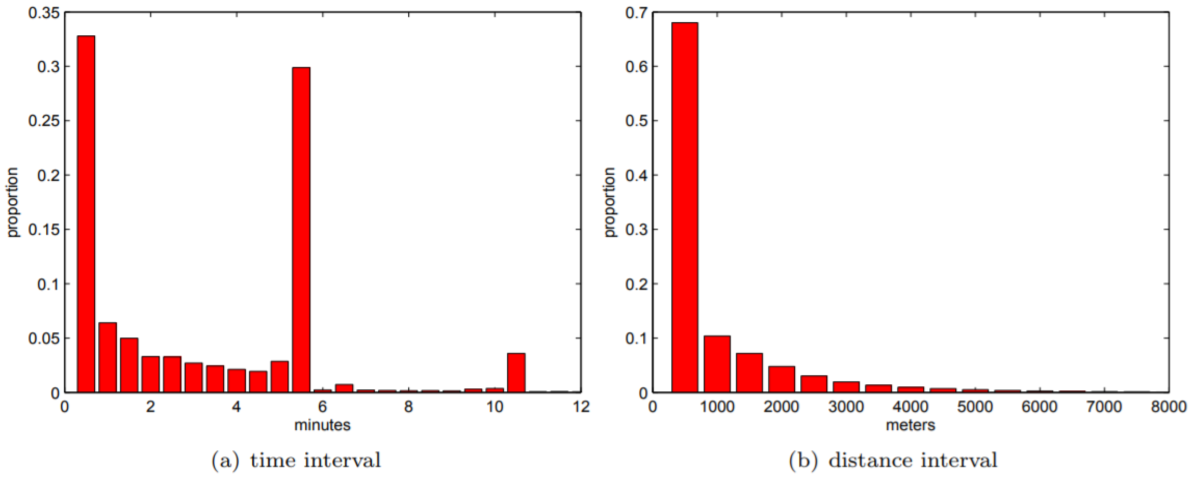


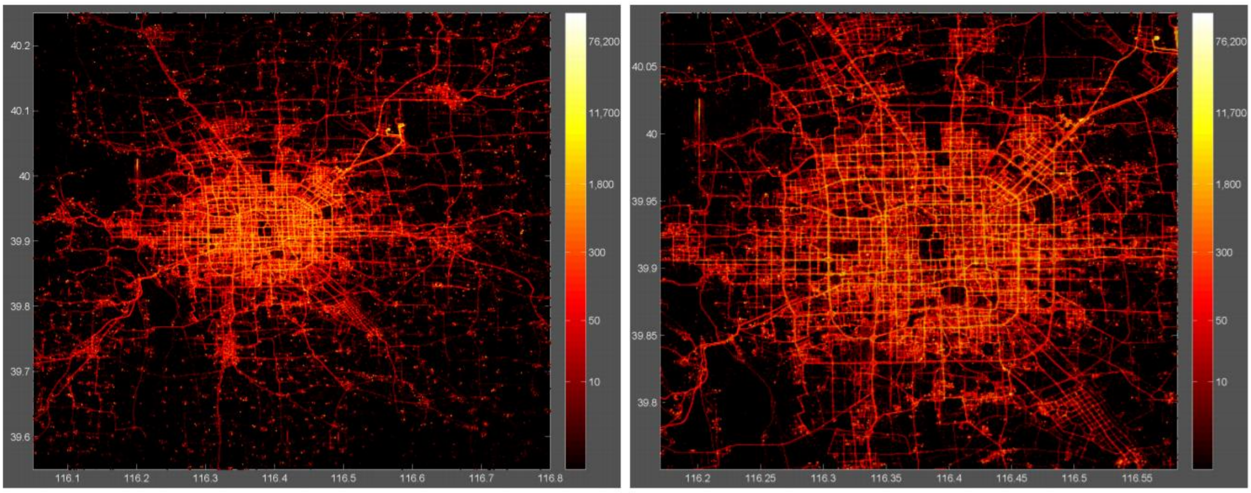
Figure 4.20. Histograms of time interval and distance between two consecutive points
<Source: Microsoft Research, 2011>

Figure 4.20 plots the distribution of sample size by time interval and distance interval between two consecutive GPS points in the sample data. As seen from **Figure 4.20(a)**, approx. 33% of the data has relative smaller time interval (less than 30 seconds), yet over 30% of the data have much longer sampling time (above 5 minutes). Profile in **Figure 4.20(b)** indicates that majority (approx. 68%) of the data have a distance interval under 500 metres. While the average

[4] T-Drive data contains real-world trajectory dataset generated by more than 33 thousand taxis in a period of 3 months (Yuan et al, 2010a). Accessible on: https://dl.acm.org/citation.cfm?id=1869807

sampling interval is about 177 seconds with about 623 metres (Zheng, 2011; Microsoft Research, 2011).

Figure 4.21 demonstrates the coverage of taxi GPS points within Beijing, showing that the data has a reasonably good geographical coverage in the city centre, but sparsely distributed in the surrounding areas (e.g. outside the Fifth Ring Road).



(a) Data overview in Beijing (b) Within the 5th Ring Road of Beijing

Figure 4.21. Distribution of GPS points
Source: <Microsoft Research, 2011>
Note: <the colour indicates the density of the points (x-axis: latitude; y-axis: longitude)>

These show that there are challenging issues lies behind the data, and require us to deliberate the study with care:

(1) Some road links or lanes are preserved for buses and taxies, and private vehicles could be restricted.

Our field survey shows that in most cases, private cars still share the same tracks as taxis. Therefore, it is reasonable to assume that taxi trips are representative for trips of other vehicles (e.g. private cars and buses).

(2) The data is sparse without full coverage of Beijing (i.e. within the Sixth Ring Road), especially in the suburban area.

The data has a comparatively more intact distribution in the central area. Therefore, we have used the trimmed data (within the Fifth Ring Road) in our analyses. We have also developed respective processing progresses to estimate the congested road speeds for links or lanes where have GPS data (**Section 4.6.1**) and where not (**Section 4.6.3**). For road links where has adequate GPS traces, the approach estimates the congested link speeds precisely using GPS-based method; for the other links, where lack the data, the speeds are estimated based on the average values.

(3) *Unlike the quality GPS data which typically registers one data point for every 10-30 seconds, the T-Drive sample data have a relatively low-sampling rate, i.e. one data point per approximately 3 minutes on average.*

To address this drawback, we have introduced pre-processing step to filter out those data with longer intervals of time or distance and hence high risks of uncertainty (**Section 4.5.2.1**). In the application of DBSCAN algorithm, we have applied a cleaning process to exclude invalid data points (with higher level of uncertainties) to better examine and testify the GPS trace data. While in the estimation of congested link speeds as part of the model development, we apply a filtering process to sift out those data points which may introduce errors or bias (such as data points with very long time or distance intervals in between), which is followed by a minimum-path inference process to allocate the crow-fly traces (between pairs of consequential data points) onto the modelled network based on the assumption of that the taxi drivers are familiar with the varying traffic conditions and would prefer the most time-efficient routes.

(4) *Over the three lead-up workdays (Monday – Wednesday) just before the Chinese New Year (Thursday), the data represents a dramatic decreasing trend in its daily total.*

As it is wonted in China to continue working until the afternoon on the New Year eve, the AM on-road traffic condition right before the festival is comparably representative for a typical neutral weekday. In addition, despite the downward trend in the number of data points, there are still substantial sample volumes from Monday to Wednesday. Hence, in the model development, we use the AM GPS points between Monday to Wednesday for the congested speed estimation.

(5) *The data lacks passenger status, i.e. it is unknown whether a taxi is empty or occupied by passengers.*

This issue makes it almost impossible to tell whether a sluggish taxi (e.g. with a speed of 0kmh) is waiting for passengers or standing still in the clagged traffic. This presents a challenge for us in using the data to estimate road link speeds, as taxi GPS traces with null speeds should only be included if they are in the congested traffic conditions, rather than other irrelevant passenger-related activities. In this case study, we exclude the taxi traces with zero speeds. This can be concerned as being biased towards higher-speed estimations. However, the verification tests indicate that the resulting estimated link speeds are reasonably accurate, and not materially affected by this issue.

4.5.2. Implementing the spatial-temporal analyses

As discusses, we will verify the sample taxi GPS data through patterns of hotspots of slow-moving and stopping taxi traces, based on spatial-temporal analyses. Here we apply the DBSCAN clustering algorithm to identify such hotspots, and in this section, we will discuss in detail the stepwise implementation of the clustering approach. The resultant patterns will be further examined in **Section 4.5.3**.

4.5.2.1. Preparation (Data pre-processing)

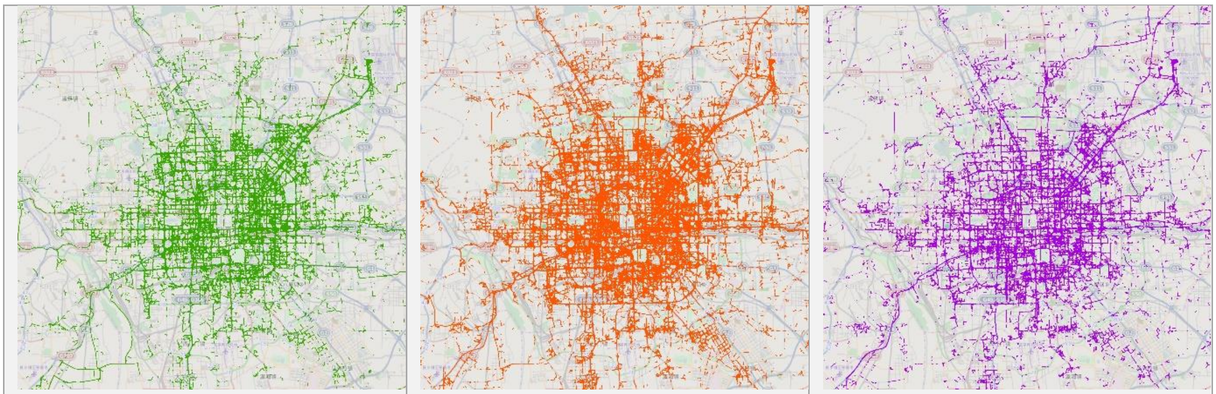
Raw taxi GPS traces need to be pre-processed before running through the analyses. This preparation consists of three steps as follows:

(1) Create crow-fly lines between each pair of consequent GPS points (generated by one same taxi within one same day). Each line inherits with features of points at both ends, allowing calculations of distance and time duration.

(2) Filter out invalid crow-fly links or links with considerable uncertainties, based on two criteria as follows:

- **Time duration is null:** a crow-fly link will be removed, if its two endpoints locate in difference places but the time duration is null (0). There are considerable uncertainties lie in such links, as the 0-duration could be caused by sampling error or signal loss; and hence this process of removal is necessary.
- **Link length ≤ 500m:** crow-fly links longer than 500m (derived through experiments associated with trial-and-error) will also be removed. Urban area in Beijing is covered with wall-to-wall road network, and the average length of modelled road links (in the strategic transport model of this study) is only about 335.2 metres. This means that between two consequential GPS data points, if the in-between crow-fly distance is considerably long, there will be various routing options than the actual one. This could introduce higher level of uncertainty in the map-matching process. To minimize the impact, it is necessary to implement this filtering process. While it is worth noting that this filter could effectively retain the GPS traces that are either move relatively slowly (i.e. short distances between footprints) or have a relatively frequent sampling interval between successive signals.

The selected links through the above filtering processes are illustrated in **Figure 4.22**, by **(a)** Weekend group, **(b)** Workday group, and **(c)** Holiday group. There are respectively 70%, 73% and 86% crow-fly links remain by each of the date groups (**Table 4.15**).



(a) Weekend (b) Workday (c) Holiday

Figure 4.22. Filtered Taxi GIS Links with Duration > 0 second and Length ≤ 500 metres

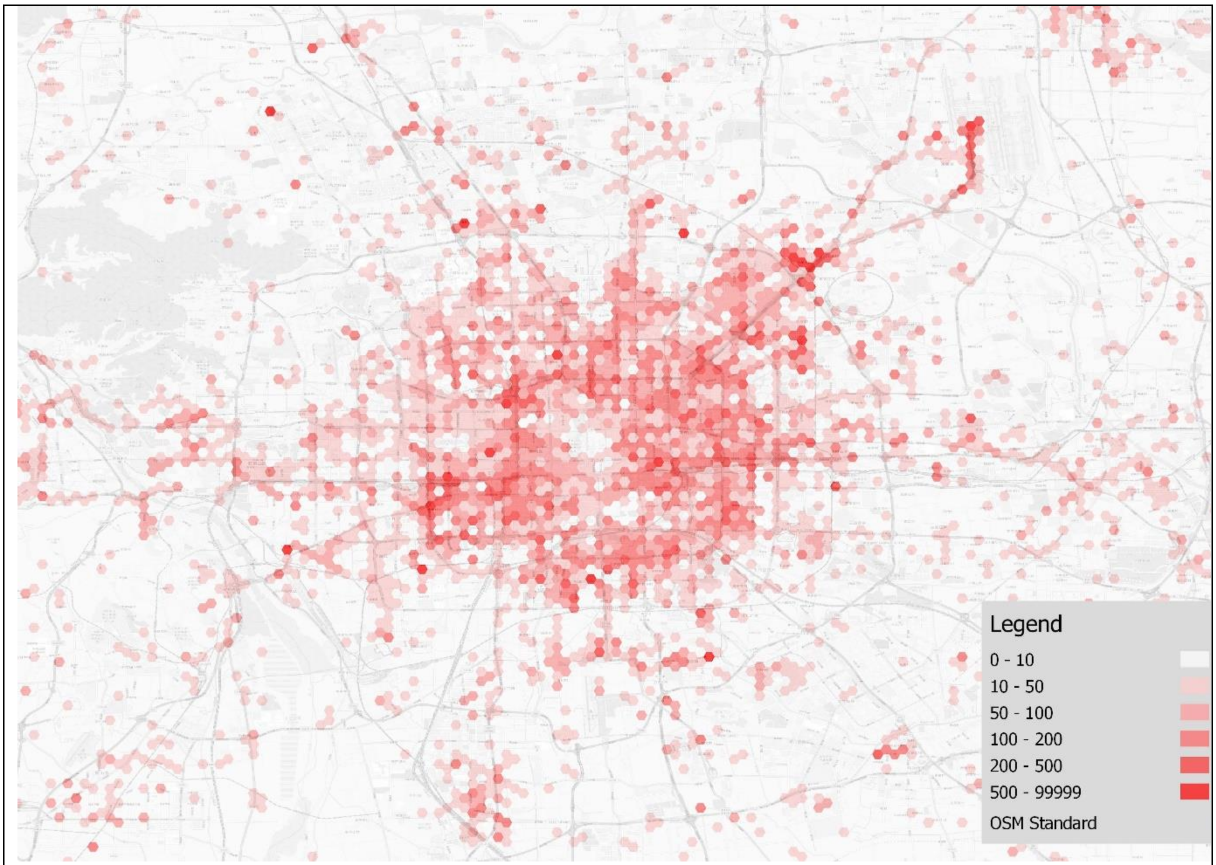
(3) Insert vertices: at every 10-metre interval, a vertex is inserted upon each of the selected crow-fly links. This step converts the selected crow-fly links into evenly distributed vertex points, providing inputting data points to the DBSCAN procedure. As the DBSCAN algorithm defines clusters based on the spatial density of data points, it is necessary to represent the crow-fly links in the format of points. Also, the average crow-fly speed is constant at any part along one same link (crow-fly speed calculated as link length divided by time duration); hence to ensure the clusters catch the entire spatial extent of each individual link (with same speed), it is important to represent each part of every link evenly and equally in distance. Therefore, through experiments (associated with trial and error), the links are represented by their vertices at every 10-metre interval. Each vertex inherits the feature from its host link, including the average moving speed, trace link length, as well as start-point and end-point timestamps. There might be concerns about that the longer a link is, the more representative vertices there will be. As the sampling rate of the GPS data is sparse and inconsistent, longer links (with more vertices) could be either towards links with faster-moving speeds or more infrequent sampling rates. But with the 500m upper limit of link length and the spatial-density-focused nature of DBSCAN algorithm, the scale of impact is unknown but could be very limited.

Through the filtering process in **(2)**, about 76% of the raw links over the morning peak hours have been sifted in total (**Table 4.15**). **Figure 4.23 - Figure 4.28** illustrate the density maps of the links before and after the filtering process for each of mornings.

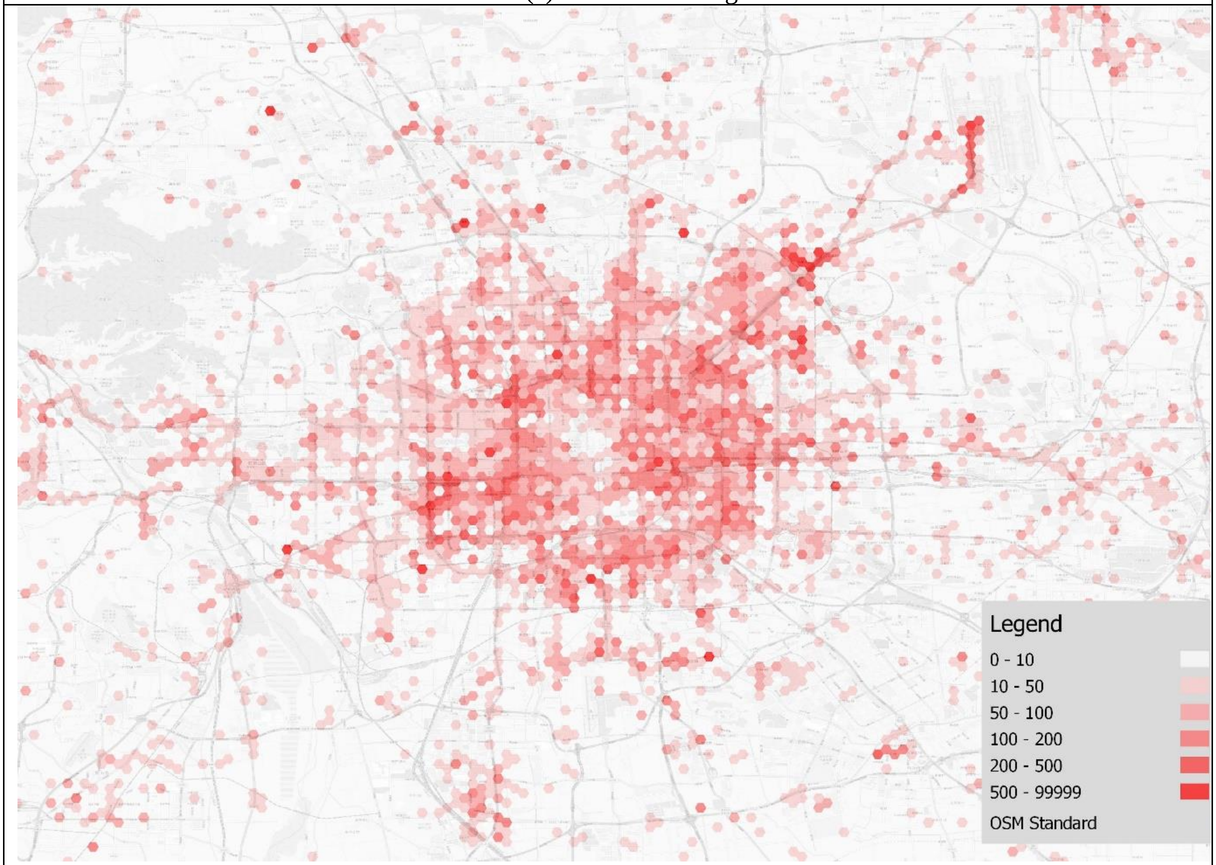
Table 4.15. Summary of filtering process

Group	Date	Count		Filtering Rate
		Before	After	
Weekend	Sunday, 2008-2-3	454,377	316,062	70%
Workday	Monday, 2008-2-4	562,612	396,112	70%
	Tuesday, 2008-2-5	509,690	364,970	72%
	Wednesday, 2008-2-6	422,795	333,853	79%
	Subtotal	*1,495,097*	*1,094,935*	*73%*
Holiday	*Thursday, 2008-2-7	389,521	337,981	87%
	Friday, 2008-2-8	415,123	352,024	85%
	Subtotal	*804,644*	*690,005*	*86%*
Total		2,754,118	2,101,002	76%

*Note: <*Chinese New Year>*

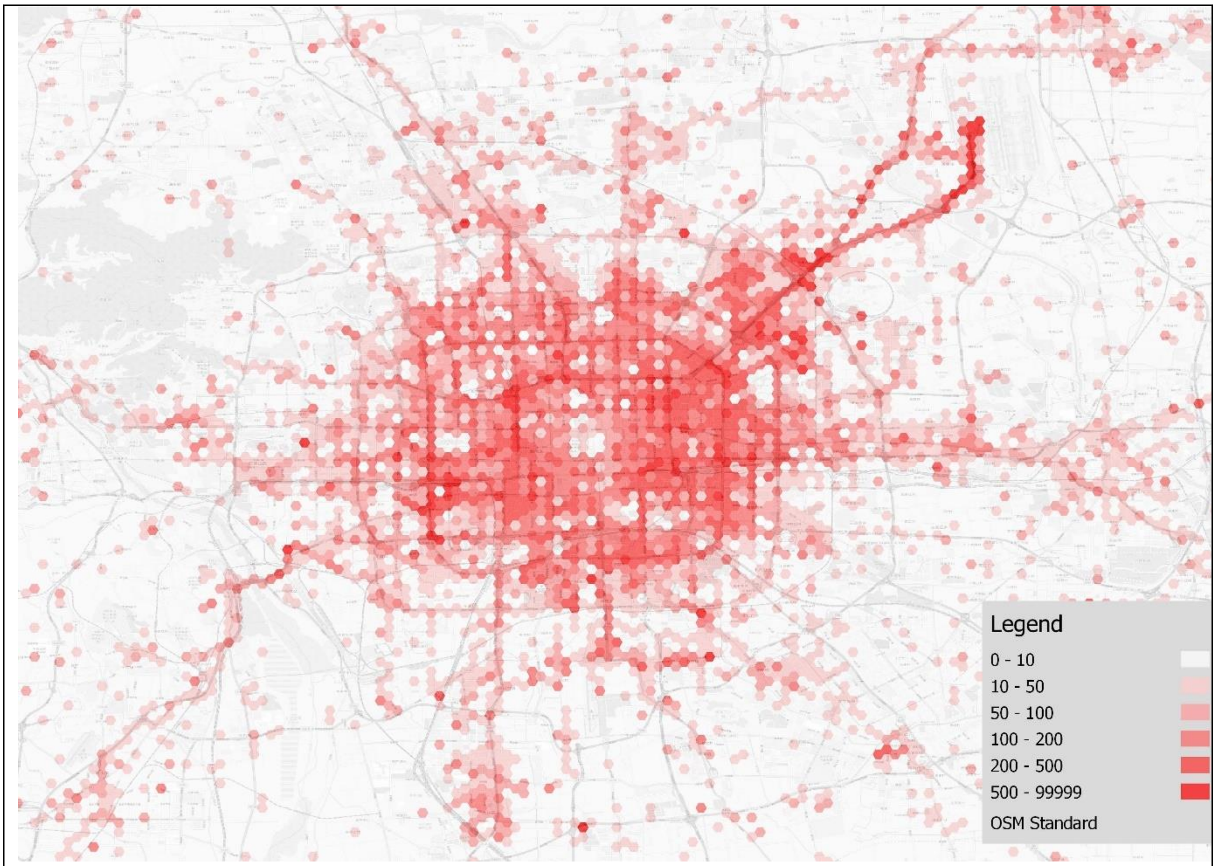


(a) Before filtering

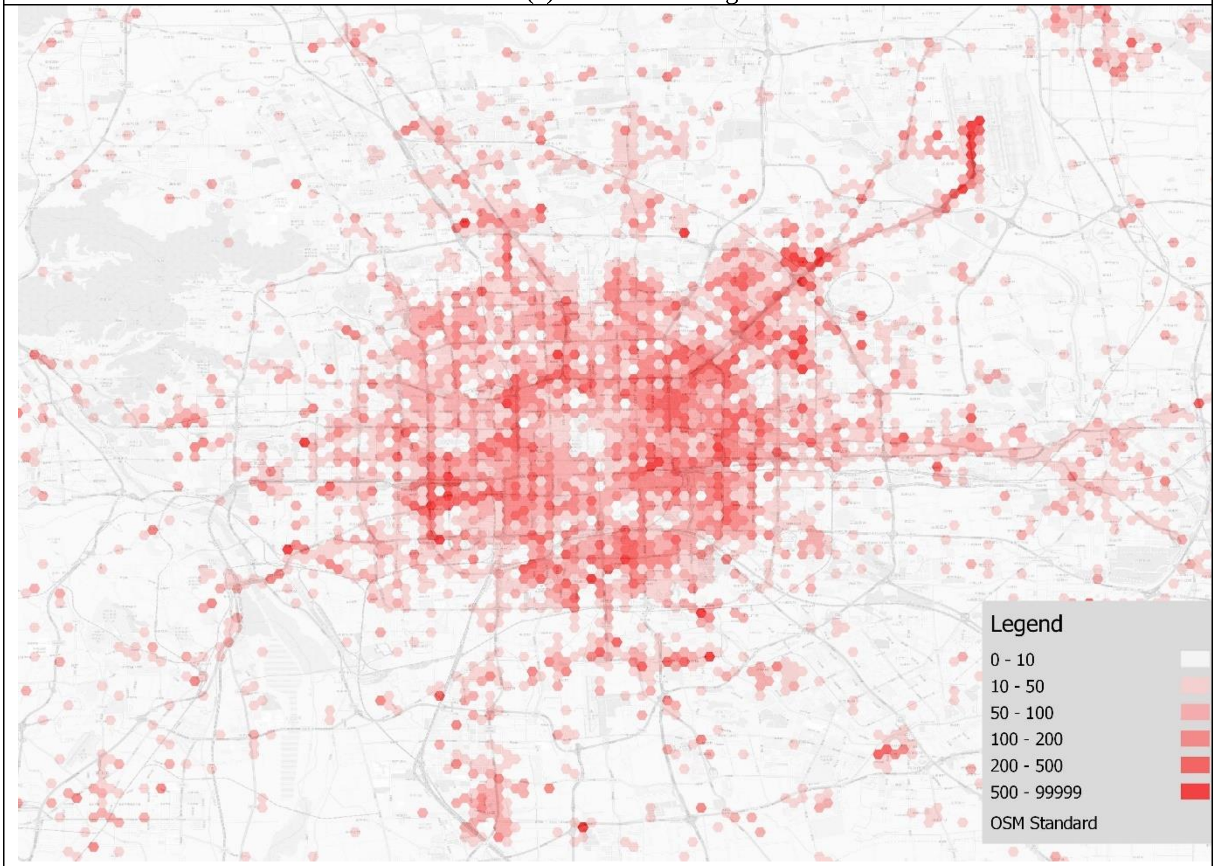


(b) After filtering

Figure 4.23. Density of taxi GIS links (Sunday 2008-2-3): before vs. after filtering

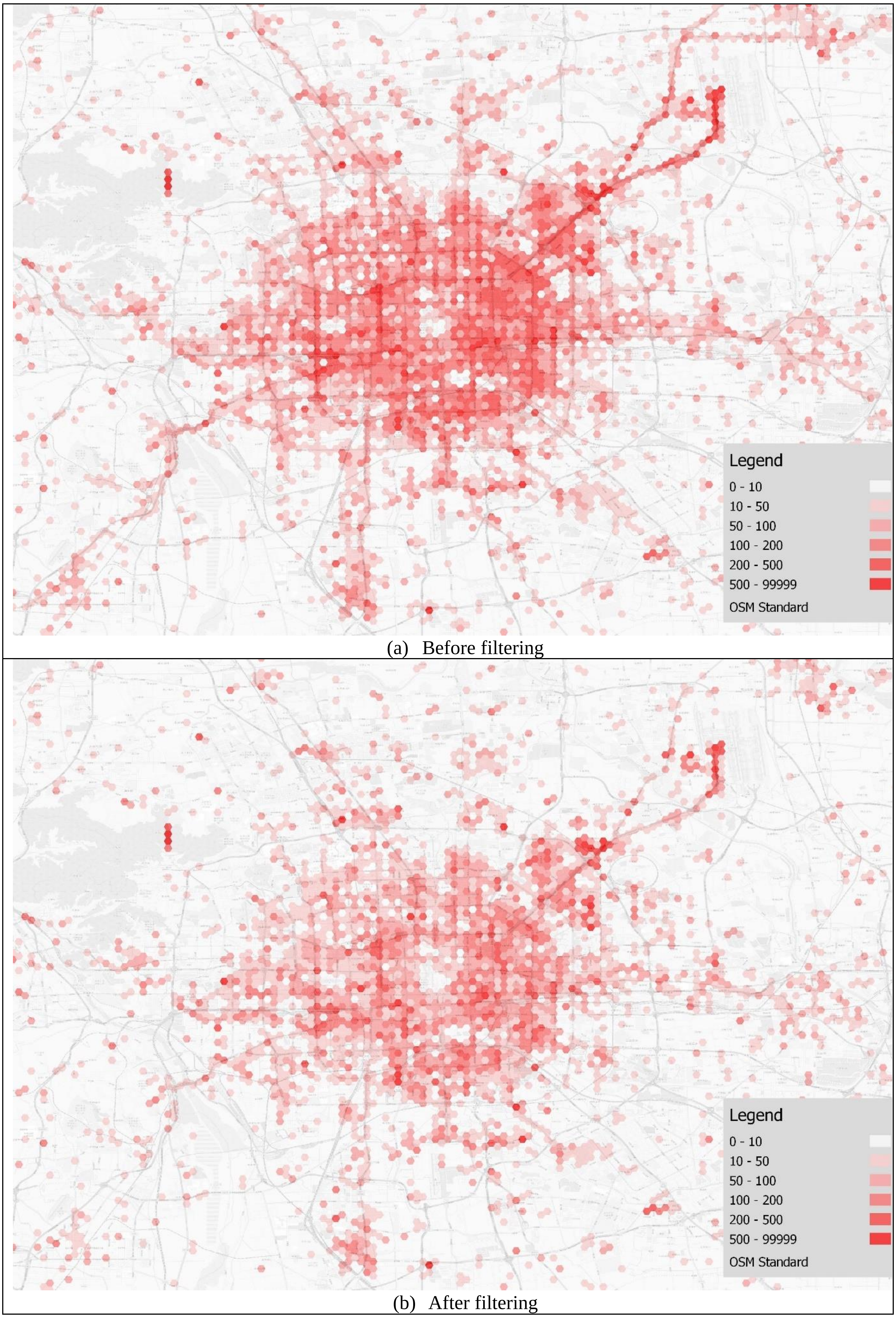


(a) Before filtering



(b) After filtering

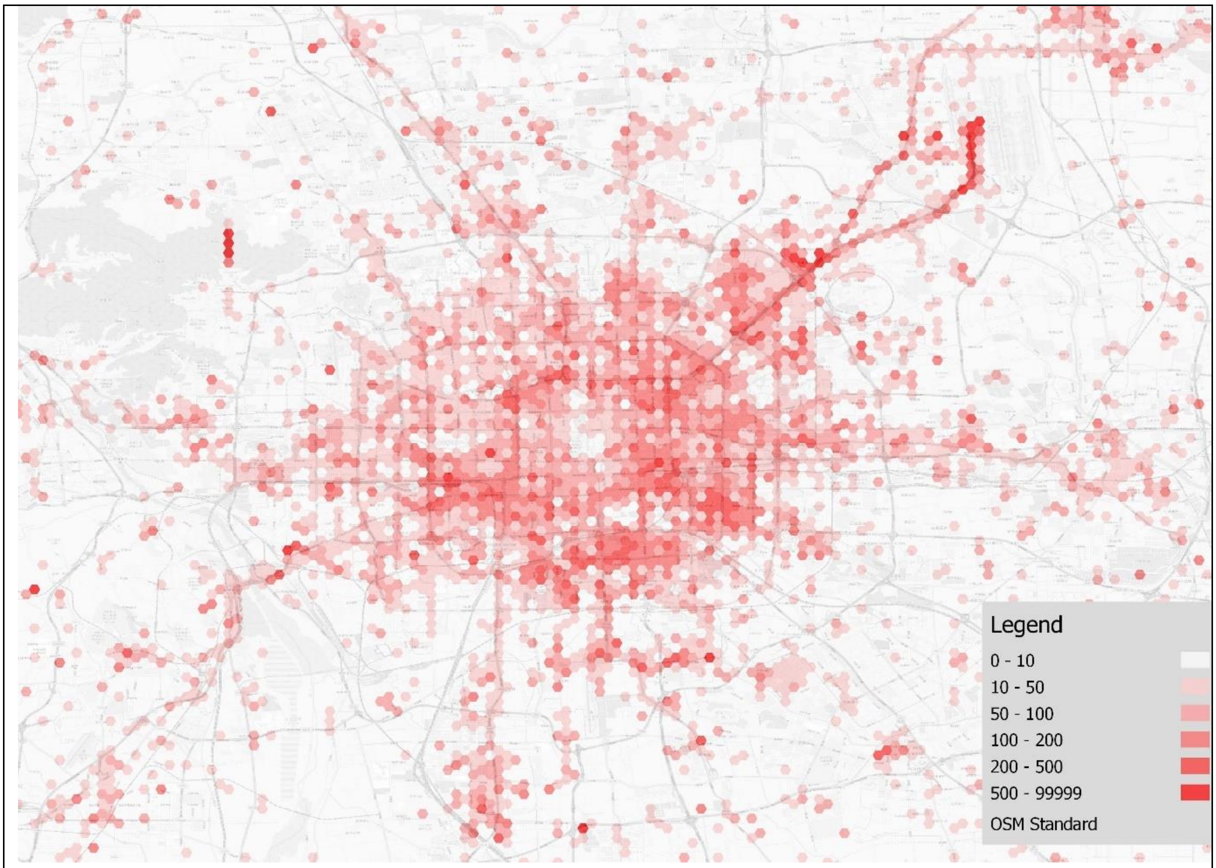
Figure 4.24. Density of taxi GIS links (Monday 2008-2-4): before vs. after filtering



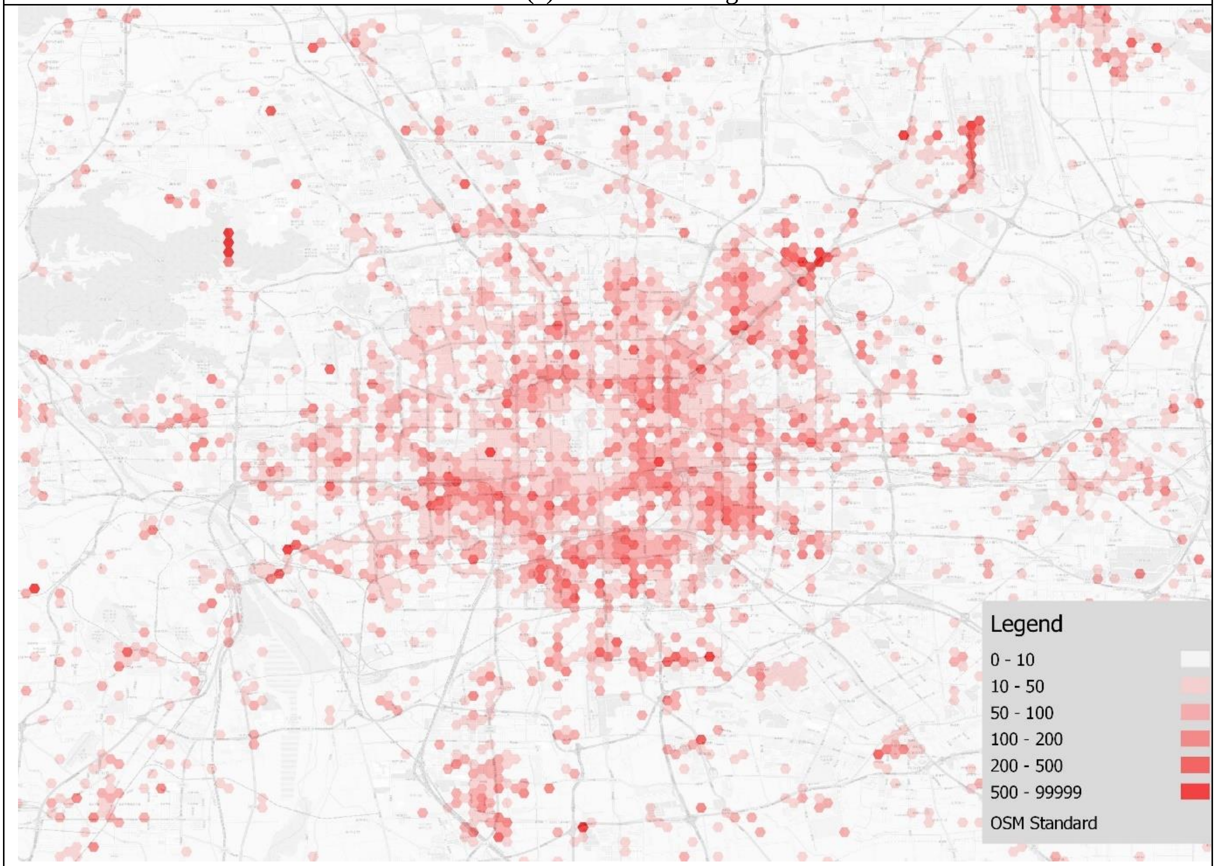
(a) Before filtering

(b) After filtering

Figure 4.25. Density of taxi GIS links (Tuesday 2008-2-5): before vs. after filtering

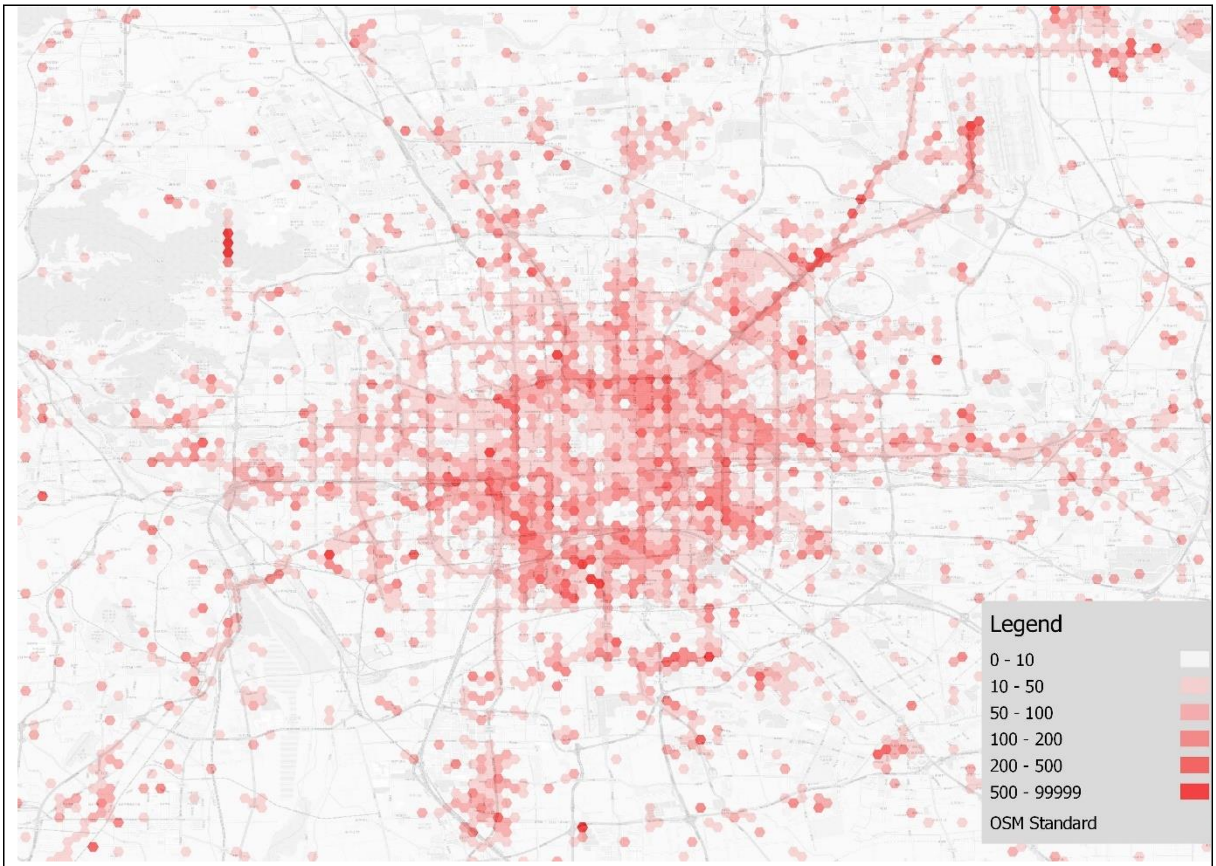


(a) Before filtering

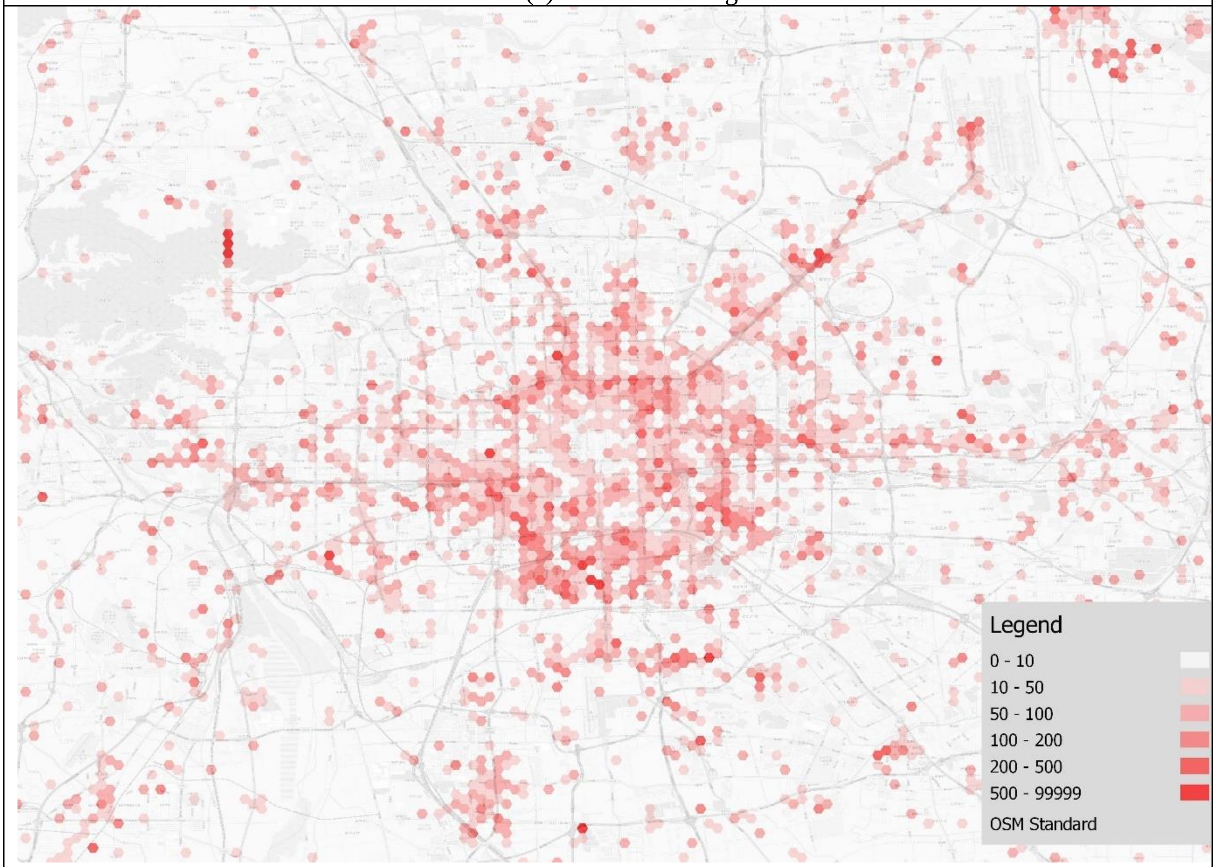


(b) After filtering

Figure 4.26. Density of taxi GIS links (Wednesday 2008-2-6): before vs. after filtering

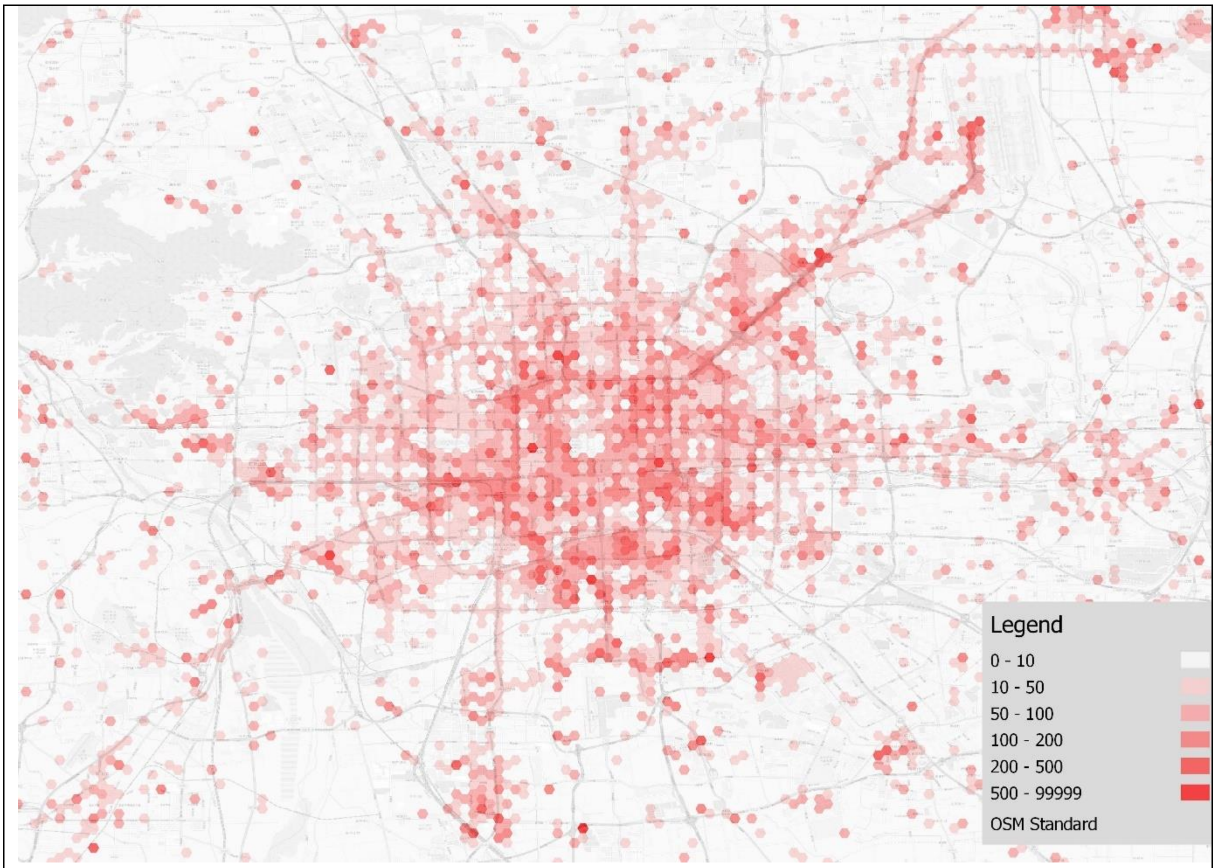


(a) Before filtering

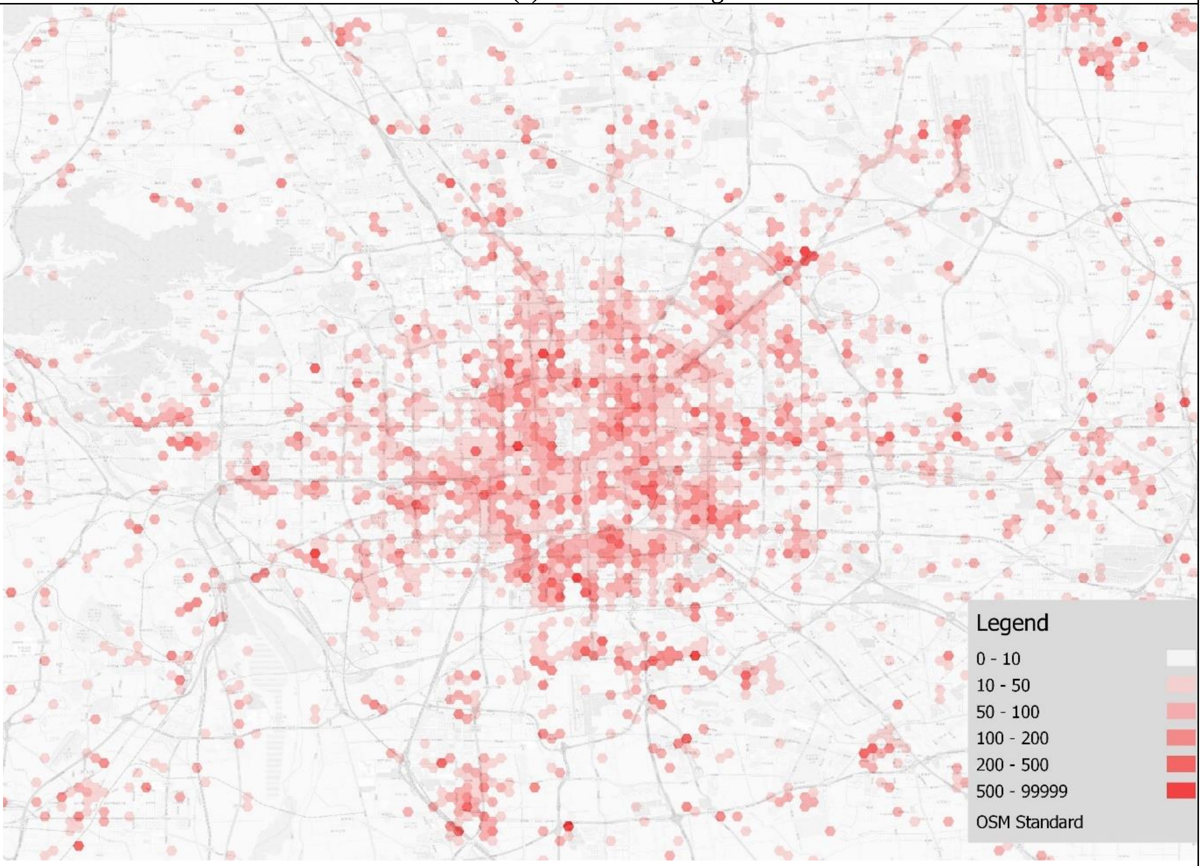


(b) After filtering

Figure 4.27. Density of taxi GIS links (Thursday 2008-2-7, Chinese New Year): before vs. after filtering



(a) Before filtering



(b) After filtering

Figure 4.28. Density of taxi GIS links (Friday 2008-2-8): before vs. after filtering

Step **(3)** transforms the GPS links into points as exemplified in **Figure 4.29** nearby Xi Zhi Men (Workday group).

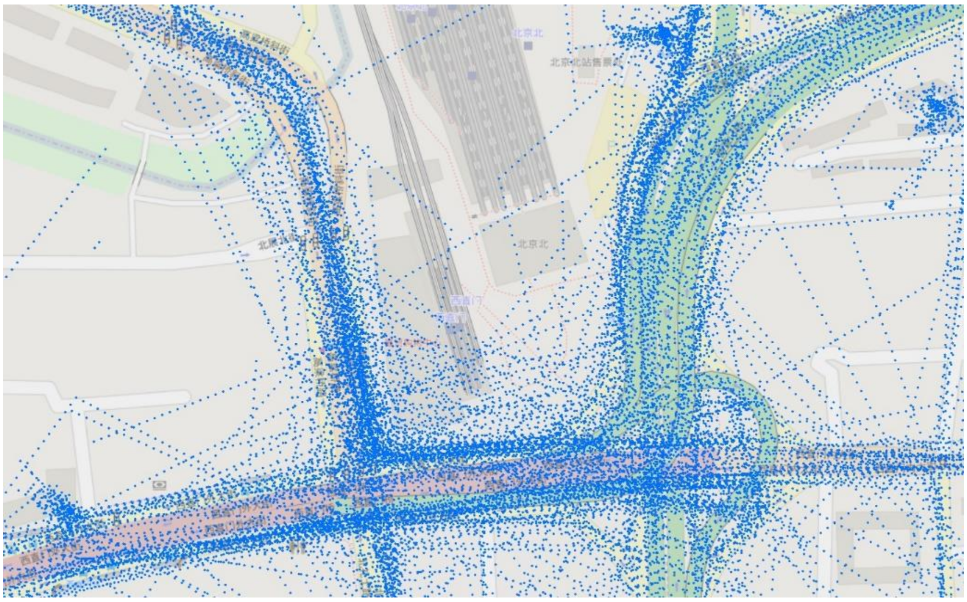


Figure 4.29. Conversion of Traces into Vertices (every 10 metres) Near Xi Zhi Men
Note: <during 6.00AM-11.00AM from 4th to 6th February 2008>

There have been 1,602,415, 5,024,268 and 2,086,005 vertices generated for Weekend, Workday and Holiday groups respectively. As the traffic conditions during morning peak hours in working days are of the most interest in this case study, in the following DBSCAN analysis, only the workday morning peak period data (with 5,024,268 counts of vertex points) is used.

Therefore, **Figure 4.30** summarises the profile link vertices in this group (Work-day group) by speed band over the AM period (every half an hour between 06.00 – 11.00AM). The total number of trace links and vertices are continuously incrementing from 6AM to 11AM on working days. The data confirms the general observation that there are more taxis in streets after 9AM (note this is often denied by taxi drivers in Beijing!). For instance, during 10:30-11:00am, there are 901,826 vertices on the road, which is about 3.7 times of those during 6:00-6:30am. The speed profile bars in **Figure 4.30** shows that slower movements (e.g. at a 2kmh speed) tend to diminish in both absolute and relative terms. This could be understood as more and more parked or resting taxis (i.e. with speeds below 2kmh) become motivated to join the street traffic as the AM peak passes.

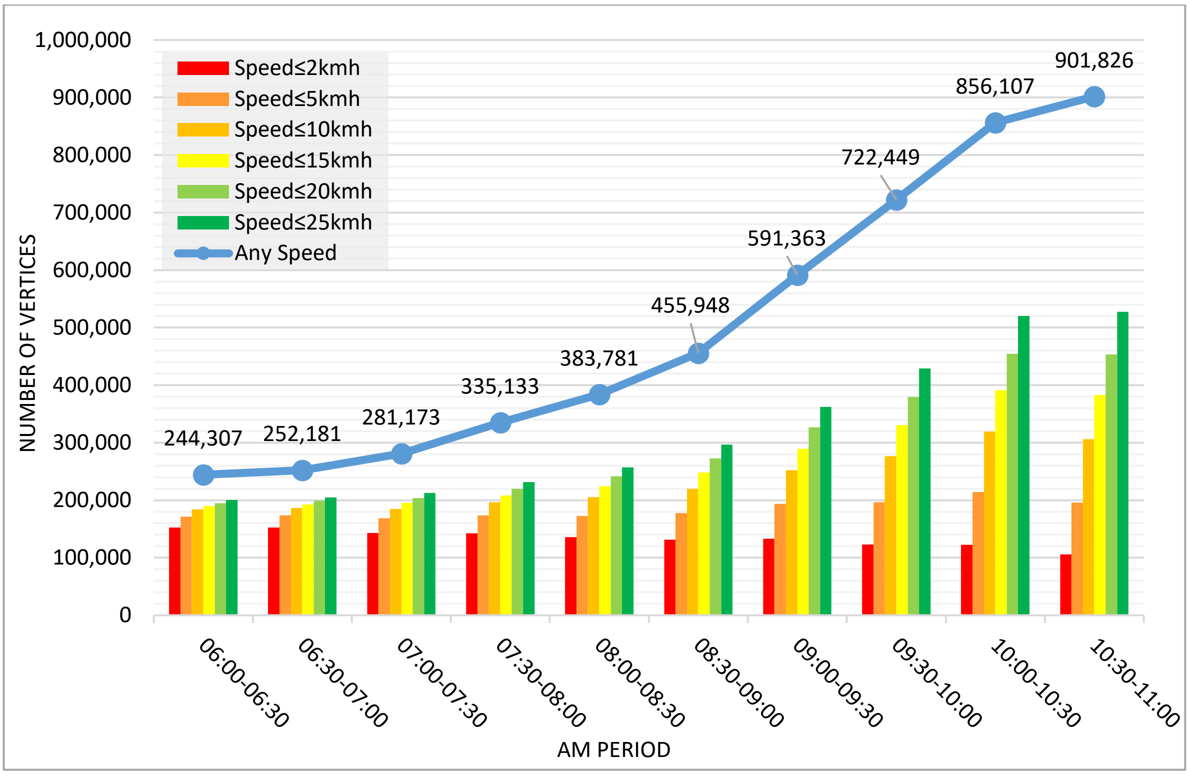


Figure 4.30. Counts and average speed profiles of the vertices by half hour period (Work-day Group)

4.5.2.2. Application of the DBSCAN algorithm by time period

The DBSCAN algorithm is applied to identify clusters of taxi traces with respective average speed ranges of 0-2, 0-5, 0-10, 0-20, 0-25mh, by each half an hour (which is in line with the general traffic management cycles) for an extended weekday morning period from 06:00 to 11:00AM (including both of the core peak hour and the shoulders).

Instead of the discrete speed bands (e.g. 0-2, 2-5, 5-10kmh…), cumulative bands (e.g. 0-2, 0-5, 0-10kmh…) have been applied to segment the clusters. This is because that a cluster with a cumulative speed band can have farthest reach of the data vertex points (from the host crow-fly taxi GPS traces) within the upper speed bound, representing a less concave and more endowed shape. This helps us with observing the clusters' temporal spatial characteristics among different locations, in comparison against the local guides (field survey).

It is also worth noting that **(1)** the 0-2kmh range includes stationary taxis (e.g. zero speeds); **(2)** the 0-25kmh group already covers data points with speeds ranging from very slow (e.g. 0-5kmh) to comparatively faster (e.g. 20-25kmh) which are well above the typical weekday morning peak speeds in Beijing City; and **(3)** in any case the above data filter will have excluded movements with higher speeds beyond 25kmh.

The two parameters, i.e. the minimum number of points (***minPts***) and the search radius ($\boldsymbol{\varepsilon}$), are both an empirical matter (which is common among all DBSCAN applications). The guidelines of the generic DBSCAN approach suggest that the ***minPts*** parameter should be the number of dimensions of the configuration plus one, and thus for this two-dimensional application we propose to set ***minPts***=*3*. The parameter $\boldsymbol{\varepsilon}$, which set to 25 metres, has been empirically tested in the case study (associated with trial and error). This means that if there are three or more vertices of the same speed range which are directly or indirectly density reachable within a maximum search distance of 25 metres, then the vertices involved are made part of a cluster.

4.5.3. Key findings of the DBSCAN clustering analysis

4.5.3.1. An Overview of DBCAN Clustering Findings

Figure 4.31 and **Table 4.16** summarise the profile and quantum of the identified clusters (or hotspots), by speed band and by half-hour interval over the extended AM peak hours (6.00-11.00AM) in case-study working days.

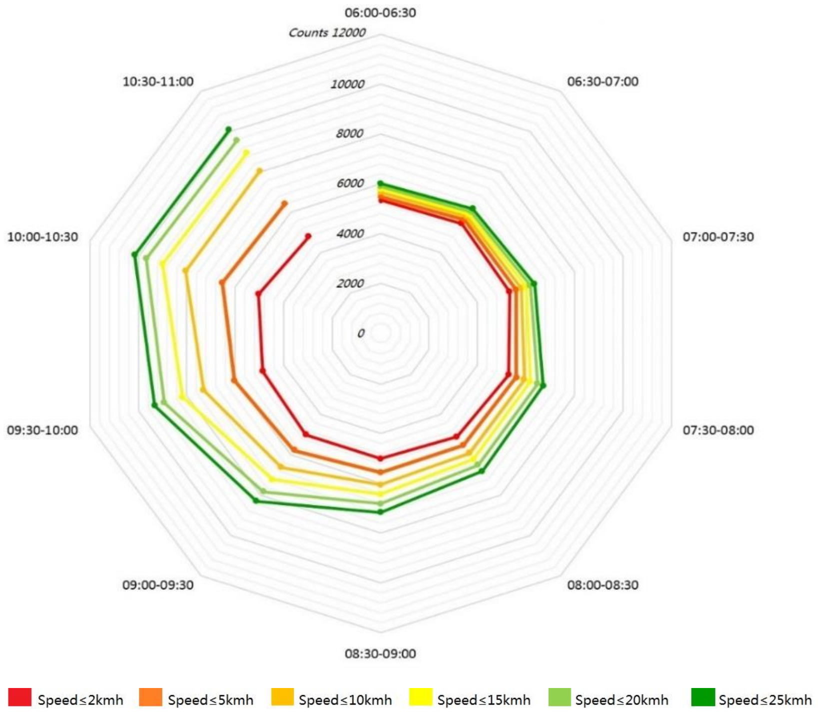


Figure 4.31. Profile of identified hotspots (clusters) by speed interval /half-hour period (Workday Group)

Table 4.16. **Identified hotspots (clusters) by speed interval /half-hour period (Workday Group)**

AM Period	0-2kmh	0-5kmh	0-10kmh	0-15kmh	0-20kmh	0-25kmh	Ratio (0-25 / 0-2kmh)
06:00-06:30	5,332	5,483	5,658	5,784	5,888	5,998	1.12
06:30-07:00	5,434	5,608	5,767	5,882	6,017	6,157	1.13
07:00-07:30	5,324	5,585	5,816	6,004	6,184	6,366	1.20
07:30-08:00	5,283	5,606	5,921	6,182	6,472	6,710	1.27
08:00-08:30	5,095	5,514	5,917	6,212	6,507	6,804	1.34
08:30-09:00	4,987	5,564	6,054	6,438	6,820	7,163	1.44
09:00-09:30	4,994	5,773	6,611	7,217	7,824	8,297	1.66
09:30-10:00	4,867	6,038	7,298	8,184	8,924	9,314	1.91
10:00-10:30	5,044	6,540	8,049	8,991	9,680	10,146	2.01
10:30-11:00	4,780	6,402	8,055	8,939	9,579	10,083	2.11
Total (06:00-11.00)	**51,140**	**58,113**	**65,146**	**69,833**	**73,895**	**77,038**	**1.51**

Maximum Minimum

In contrast to all other speed groups (which have an incremental trend in the number of clusters from 6AM to 11AM) , 0-2kmh group has an decreasing number of clusters over the period (i.e. the number of clusters approaches climax, 5434, at 6.30-7.00AM; then drops gradually until the lowest point, 4780, at 10.30-11.00AM). Clusters in this speed group (0-2kmh) represent hotspots of stationary and laggard taxi traces, and the steadily shrinking tendency for their counts indicates that the spatial distribution of plodding taxis becomes more and more sparse over time. This observation reflects closely the operational patterns of the taxis in the morning in Beijing: a large number of the taxis tend to pause the service or rest around 6.30-7.00AM which for some might also involve a driver shift-change, and then as the morning rush hour finishes, more and more taxis join the traffic. It is useful to bear this pattern in mind when further processing the data.

Another observation is that the differences in hotspot counts among different speed groups widen as time moving on. This widening variation is even more obvious in terms of comparison between the two extremes, i.e. the 0-2kmh range versus the 0-25kmh. As shown in **Table 4.16**, during the first half hour 6-6.30AM, there are 5998 counts of 0-25kmh hotspots and 5332 counts of 0-2kmh hotspots, and the ratio between these two figures is 1.12. This implies that there are approximately an equal number of quasi-stationary taxis to relatively fast moving ones (since the road network has not seen the peak hour traffic yet). Before 9:00AM, this ratio keeps below 1.5 (1.44 during 8.30-9.00AM, with 7163 25kmh hotspots and 4987 0-2kmh hotspots). The ratio significaly jumps up over 2 during 10:00-10:30AM (2.01, 10146 0-25kmh hotspots and 5044 0-2kmh hotspots), and reaches the peak value during 10:30-11:00AM (2.11, 10083 25kmh hotspots and 4780 0-2kmh hotspots).

Such two observations both indicate that most of the taxi drivers would prefer to rest or park somewhere with a very slow speed (below 0-2kmh) or not even move at all in the early morning (before 7AM). The taxis become more and more active after 7:30AM, and the taxi hotspots data is best represented during 10-11AM.

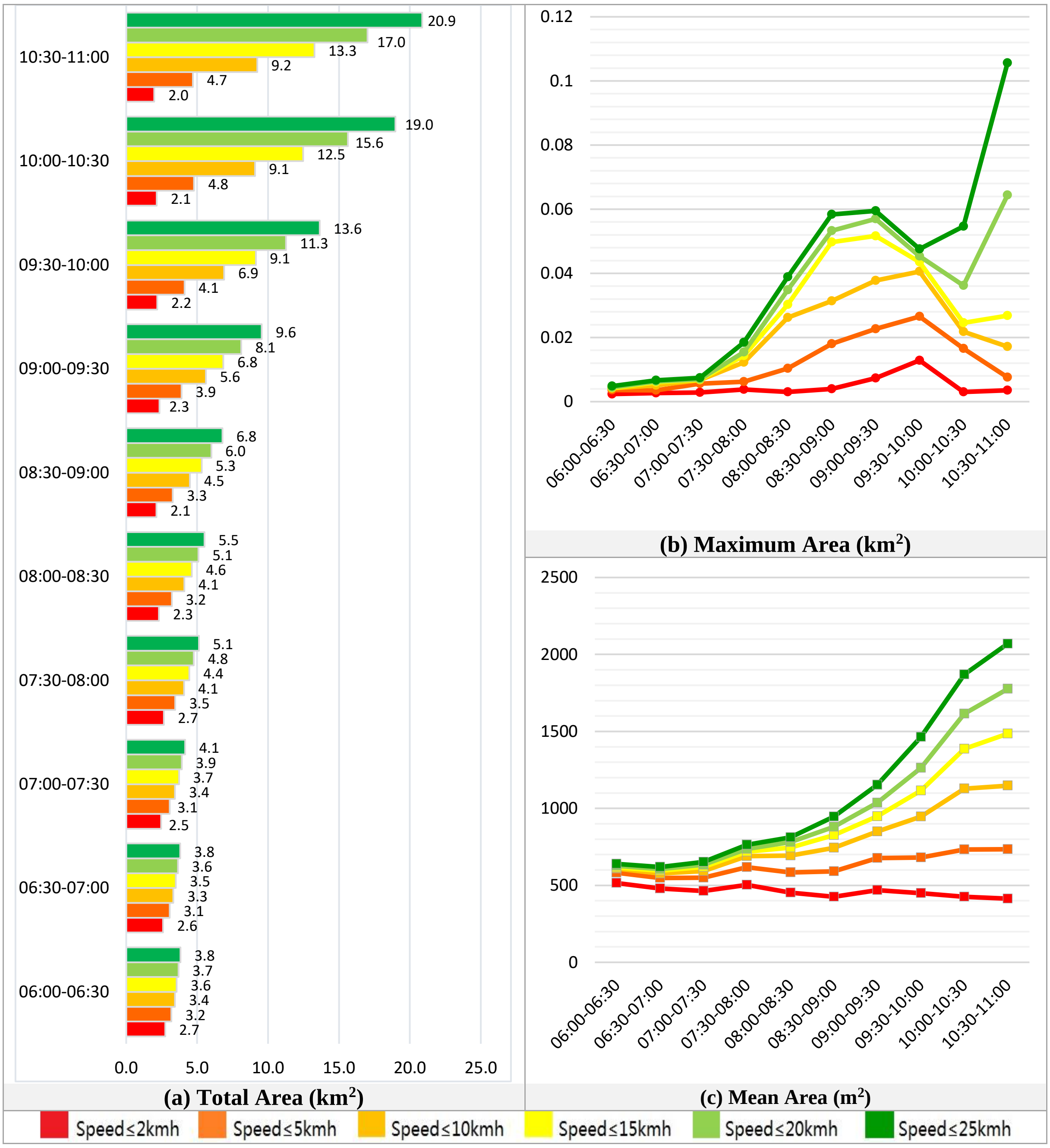


Figure 4.32. Area of identified hotspots (clusters) by speed interval /half-hour period (Workday Group)

Figure 4.32 and **Table 4.17** examine the statistics of hotspots' areas by every half an hour duing the morning peak in the perspective of area. As cumulative speed bands are used (e.g. 0-2kmh, 0-5kmh, 0-10kmh, …), the examination investigate what time the hotspots within a specific speed band are most likely to emerge, and whether the upper speed within the speed band is more widely generic in the network (a lower Standard Deviation) or more concentrated at a fewer places (a higher Standard Deviation).

Figure 4.32(a) demonstrates the total spatial coverage (area) of the identified hotspots in each speed and time segmentation, the total area for 0-2kmh shrinks steadily after 7:30 AM, from 2.7km^2 to around 2km^2. This affirms our first observation above that the quasi-stationary taxis become more and more sporadically distributed on the network over time (after 7:30AM).

The spread of the hotspot areas can provide further diagnostics. For instance, hotspots with greater areas covers more densely distributed taxi traces. Hence, in the landlocked road traffic (lower speed ranges), the maximum areas of hotspots can provide an indication of how bad the worst situation is; while in other cases (such as stationary at resting areas, or march at higher speeds), the maximum areas of hotspots in specific speed and temporal ranges are also indicative for how pleasing a crowded location is. As shown in **Figure 4.32(b)**, the maximum areas of lower speed groups (i.e. 0-2kmh, 0-5kmh and 0-10kmh) start stretching steadily from 7AM and reach climax between 9.30-10AM; while in higher speed groups (i.e. 0-15kmh, 0-20kmh, 0-25kmh) the maximum areas also begin to rise from 7AM, but much more sharply and peak at 9-9.30AM. During the hour from 9AM to 10AM, the spatial coverage of slow moving taxis is spreading, while the coverage of fast moving taxis tends to be shrinking. Such situation may be gradually relieved after 9:30AM, and the maximum area of the fast moving traffic reaches climax when it is close to 11AM. It is worth noting that, traffic hotspots with slower speeds could be related to a variety of different situations which is by no means limited to traffic congestion. This will be made clear in the next subsection.

Table 4.17. Standard Deviation of the area (m^2) of identified hotspots (Workday Group)

CLASS	QUASI-STATIONARY	SLOW		REASONABLE		
AM Period	**0-2kmh**	**0-5kmh**	**0-10kmh**	**0-15kmh**	**0-20kmh**	**0-25kmh**
06:00-06:30	1011.14	1332.21	1459.99	1489.47	1555.42	1687.26
06:30-07:00	986.10	1335.55	1545.61	1658.95	1707.25	1818.87
07:00-07:30	1121.94	1651.28	1862.22	2026.40	2107.98	2203.01
07:30-08:00	1166.33	1804.00	2701.64	3114.17	3292.11	3726.63
08:00-08:30	1027.12	2315.97	4372.75	5059.68	5611.41	5965.02
08:30-09:00	1142.36	3082.80	4933.11	7092.91	7603.03	8291.90
09:00-09:30	1470.43	3896.79	6064.18	7496.14	8035.33	8566.72
09:30-10:00	2208.17	4171.64	5980.88	6899.93	7628.74	8639.35
10:00-10:30	1165.54	3279.00	5458.37	7353.92	9252.13	12878.95
10:30-11:00	1121.19	2515.97	4951.81	7881.62	11831.57	17354.56

Similarly, the mean area of clusters with 0-2kmh speeds (**Figure 4.32(c)**) can be understood as the trend of the average slow-moving situation over morning peak. This figure can be considered together with the standard deviations (**Table 4.17**). Based on the similarity in patterns, the six speed ranges are seperated into three categories: the first category could be named as ‘Quasi-stationary’ with a <2kmh maximum speed, the second category is the ‘Slow’ with a speed range of 0-10kmh speed, and the remaining three speed ranges (between 0-25kmh) could be considered as a ‘Reasonable’ category.

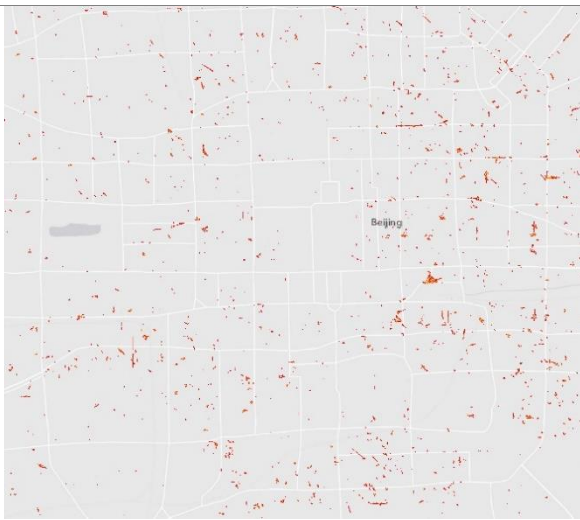
Firstly, the curve of the quasi-stationary class (0-2kmh in **Figure 4.32(c)**) is the only one which has a declining trend in mean area over the morning periods. During 6:30-7:00AM, this category has a comparatively high mean area (479.31m^2, third highest over the 10 half hours) but also the smallest standard deviation of 986.10m^2 (**Table 4.17**). This further confirms that during this half hour, there are many taxis that are parked or hardly moving. While in contrast, between 9:30AM to 10:00AM, such a distribution becomes less obvious: the mean area of quasi-stationary clusters declines to 449.57m^2 (0-2kmh in **Figure 4.32(c)**), but their standard deviation reaches the highest peak at 2208.17m^2 (**Table 4.17**).

The second ‘Slow’ category (0-10kmh) experiences a moderate growth in mean area (**Figure 4.32(c)**) over the periods, and the trend lines for the two constituent speed ranges (0-5 and 0-10kmh) reach their highest values during 10:00-11:00AM. In terms of the standard deviations, they both start to increase from the beginning of the morning and then peak during 9:00-10:00AM (**Table 4.17**). These mean that from 9:00AM, the distribution of hotspots with slow speeds in aspect of areas becomes increasingly concentrated; right afterwards during 9:30-10:30AM, the mean area of those slow moving (0-10kmh) hotspots increase rapidly, and this growth peaks at 11:00AM. In reality, the explanation for such a phenomenon may invovle some heavy congestions, unpleasant traffic lights, or passenger-loading/unloading activities.

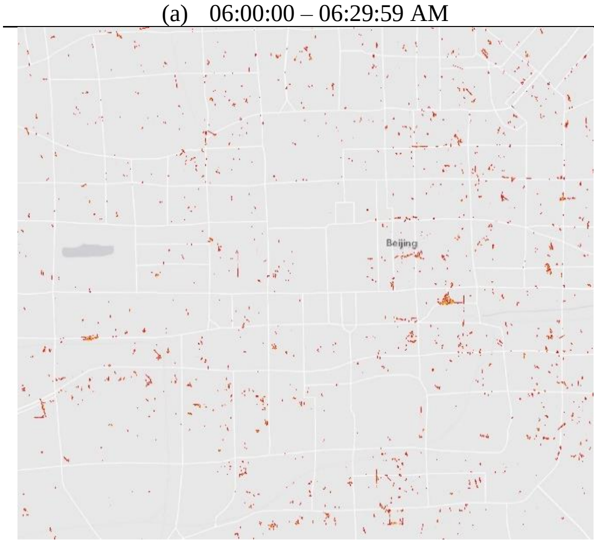
The last ‘Reasonable’ catogory (0-25kmh) has the most significant jump in mean area over the AM periods (**Figure 4.32(c)**). Also its distribution increasingly spreads over the morning period with an upward trend towards 11:00AM. This suggests that as the core rush hour finishes, the clusters of more reasonable speeds (0-25kmh) become more common in the urban area.

4.5.3.2. Distribution of individual taxi traffic hotspots

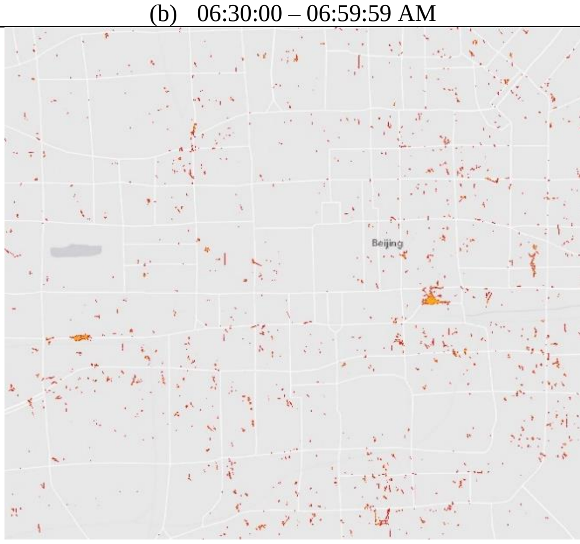
(a) 06:00:00 – 06:29:59 AM



(b) 06:30:00 – 06:59:59 AM



(c) 07:00:00 – 07:29:59 AM



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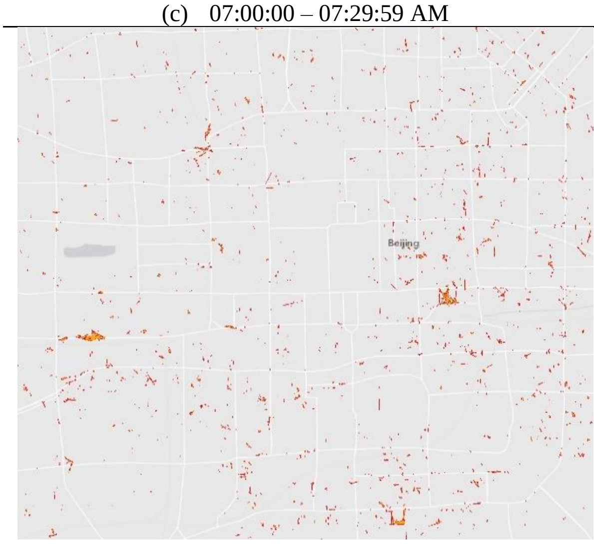
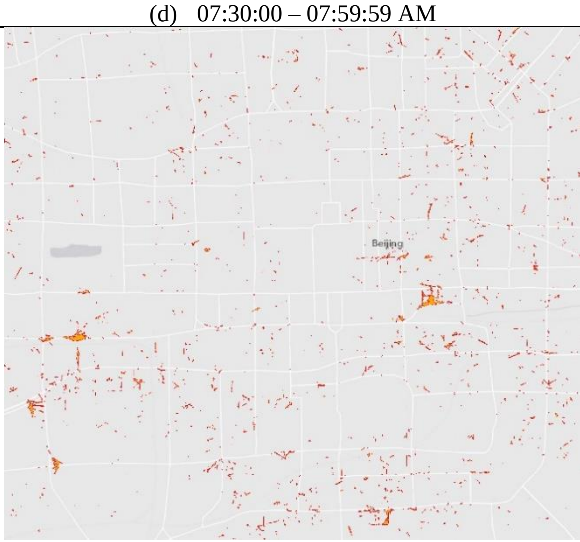
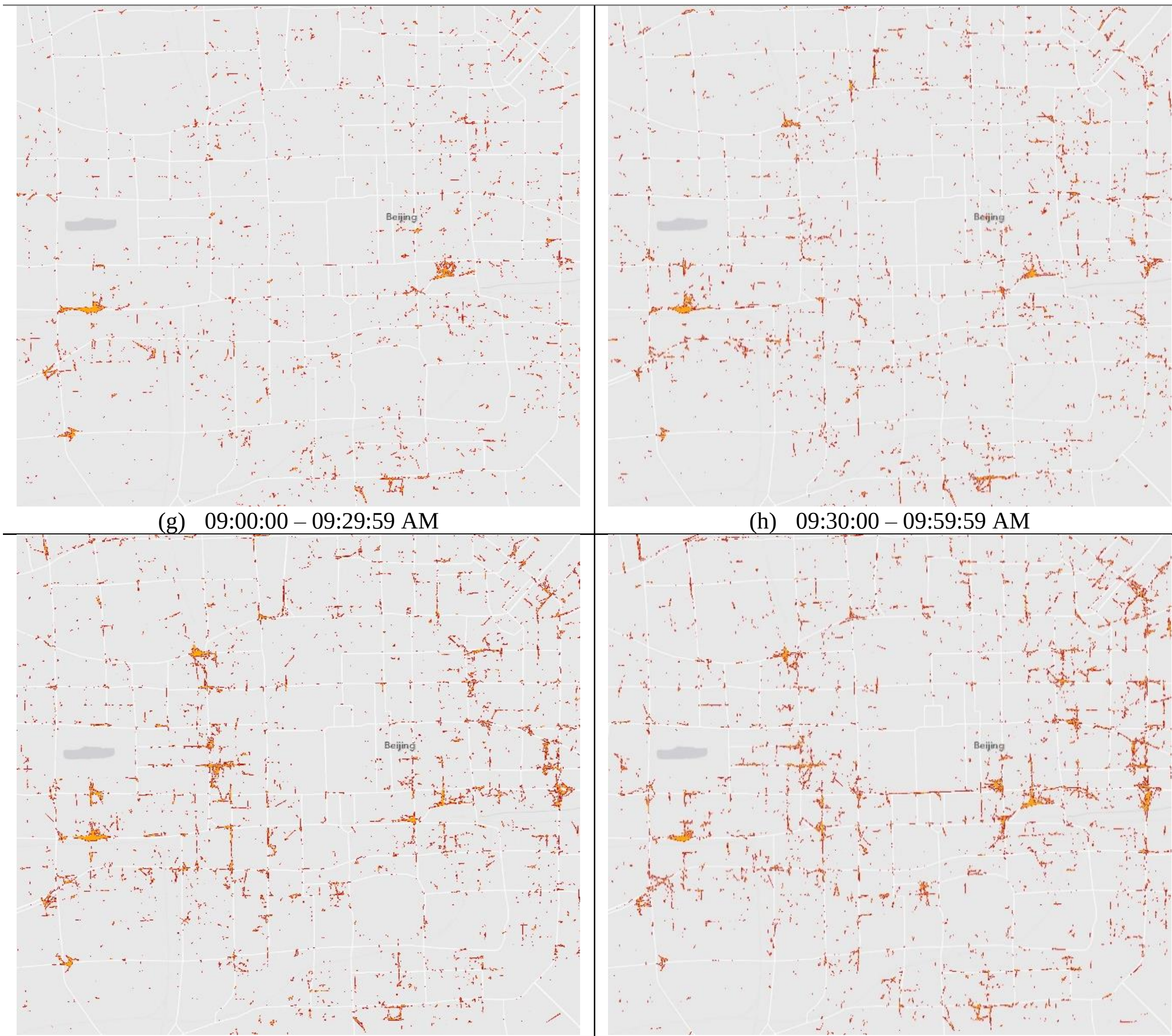


(e) 08:00:00 – 08:29:59 AM



(f) 08:30:00 – 08:59:59 AM



(g) 09:00:00 – 09:29:59 AM

(h) 09:30:00 – 09:59:59 AM

(i) 10:00:00 – 10:29:59 AM

(j) 10:30:00 – 10:59:59 AM

Figure 4.33. 0-10kmh Speed Range Hotspots within the Second Ring Road (Workday Group)

Based on the overview of the hotspot identification data, we further choose a respresentative speed range of 0-10kmh to investigate the distribution of individual taxi hotspots. On balance, the location of hotspots in this speed range is expected to highlight where and when the taxies tend to move slowly (below 10kmh) on the network, while their scales with respect to the coverage area could reflect how intensive the slow-driving activities are (such as related to traffic congestion, traffic lights or passenger-loading and unloading). Note that the clustering process is based on crow-fly GPS links (between pairs of consequential data points), which may not reflect the exact movement trajectory of the taxis; and as a result the clusters may not follow the actual road space boundaries. However, this imprecision is unlikely to affect the fundamentals of the cluster analsyis here. The maps of the ten half-hour periods within Beijing Second Ring Road are shown in **Figure 4.33**. As the time moves on, the visualisation of the clusters shows that arround the two railway stations (Beijing Railway Station and Beijing West Railway Station), there are more and more hotspots identified with increasing scales, indicating increasing activities of passenger set down, loading and associated congestion on parts of the road spaces nearby. On the other hand, the 0-10kmh hotspots also become much more noticeable on the major road links and major junctions, such as on the Third Ring Road, around Xi Zhi Men to the northwest of the Old City, and Guo Mao junction to the east, etc. The analysis of the overall patterns of increasing taxi traffic throughout the morning periods are also reflected.

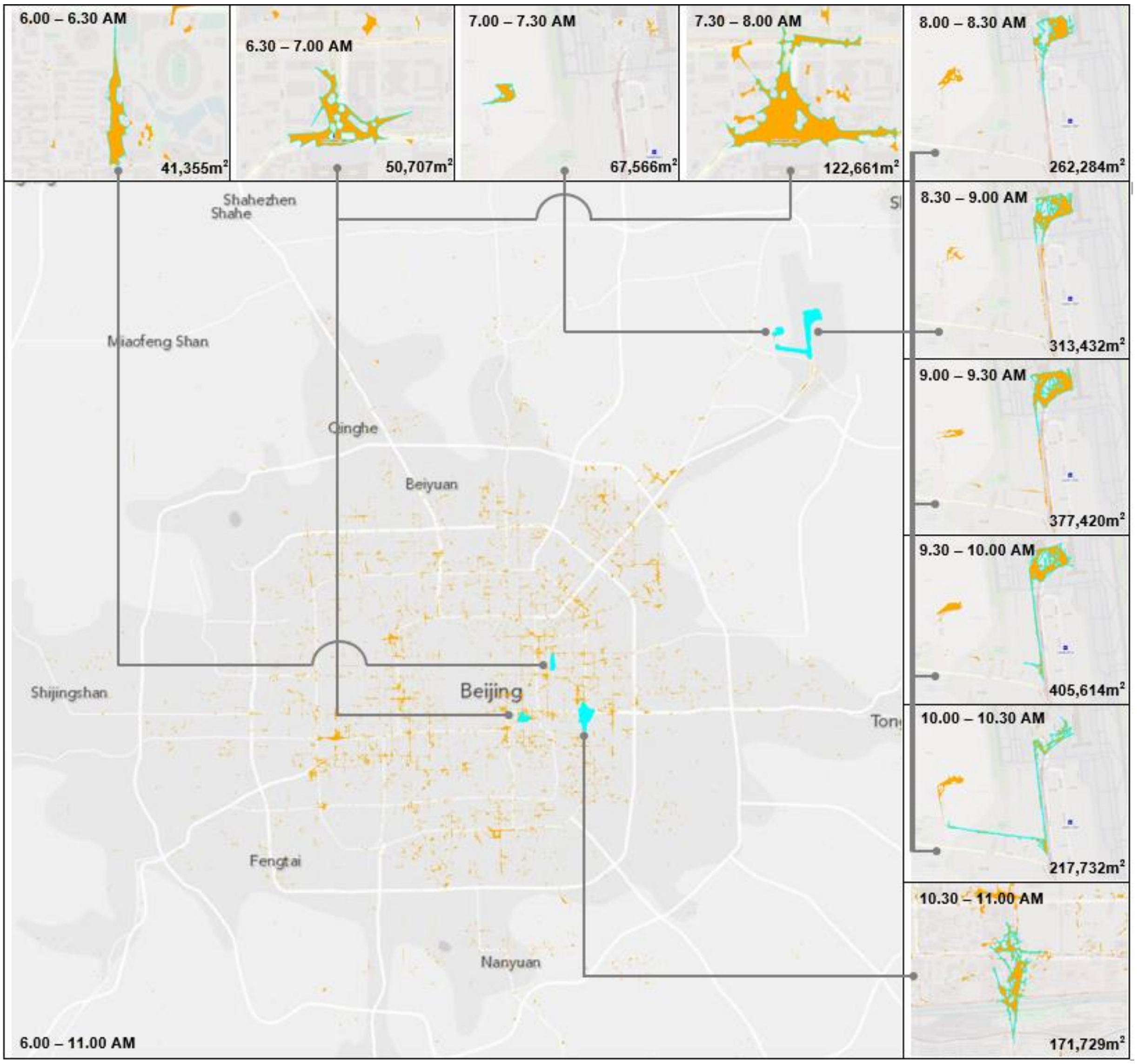


Figure 4.34. Largest hotspots of 0-10kmh speed range (Workday Group)

In terms of the largest 0-10kmh hotspots, their locations and scales over time are shown in **Figure 4.34**, for the main built-up area of Beijing beyond the third ring road. In early morning during 6:00-6:30AM, the data shows that the largest hotspot is located along the Workers' Statium West Road. During the following half hour, the largest hotspot moves to the road link right in front of Beijing Railway Station Square (Beijing Station West Road and Beijing Station East Road). Later in 7:00-7:30AM, the taxi parking area near Terminal 2 of the Beijing Captial International Airport becomes a prominent hotspot, which we think is because this parking area was used at the time for taxis to queue for loading passengers at Terminal 2 (Note that the week for the taxi data was just before Terminal 3 of the Beijing Capital International Airport was opened; Terminal 2 was therefore the main air terminal for the airport at the time this taxi data was collected). During 7:30-8:00AM, the largest hotspot appears at the Beijing railway station with a much larger scale. Over the next five half hour periods, the largest hotspot stays at the Capital International Airport, with its size reaching the largest value of 405613.5m^2 during 9:30-10:00AM. While in the last half hour, Beijing's CBD area nearby the Guo Mao junction becomes the biggest hotspot.

Besides the largest hotspots, the apperence of hotspots changing over time near some other commonly known busy traffic areas are also of direct interest to our analysis. The majority of the hotspots confirm well to the day to day observations in Beijing, which indicates that the taxi dataset is representative of the operations in Beijing at the time. Here we further investigate a few of the biggest hotspots in public road space and road junctions with a view to understand the drivers behind the slow moving taxi traffic. The areas include three major transport hubs and four well-known junctions with heavy traffic congestion.

- ***Three transport hubs***

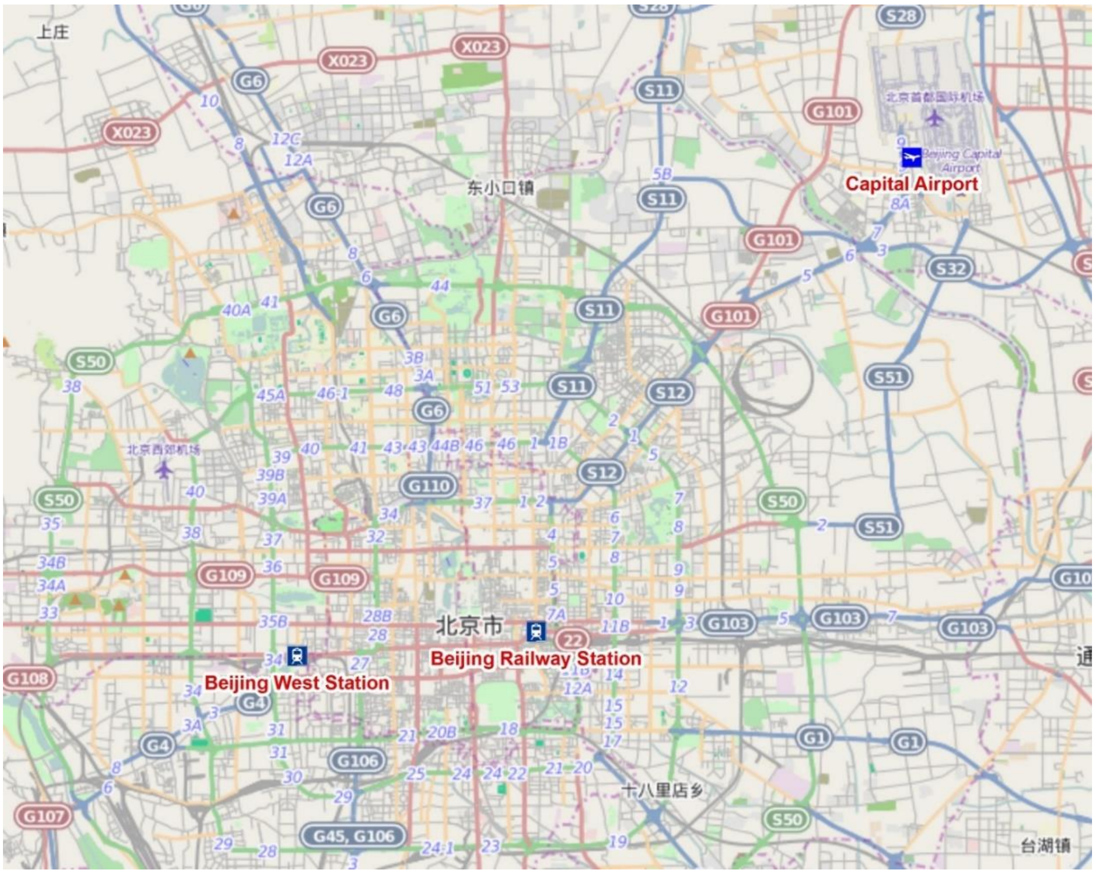
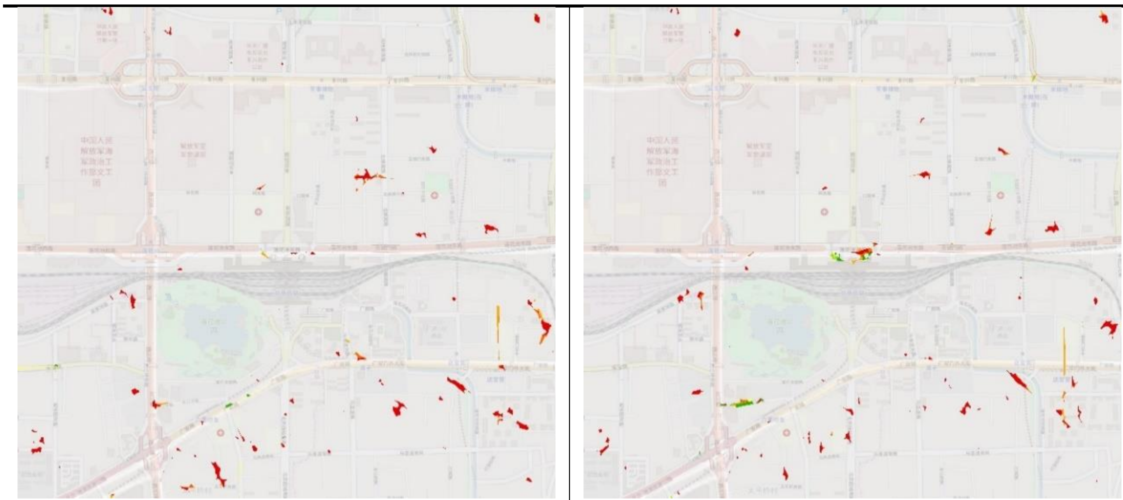


Figure 4.35. Selected Transport Hubs for taxi hotspot investigation

The selected transport hubs include Beijing West Railway Station, Beijing Railway Station, and the Capital International Airport (**Figure 4.35**). These three places have been the busiest transport hubs, and this continues today. By virtue of the massive number of taxis operating to and from the hubs and the abundance of our personal experience in using local taxis, we expect that the three transport hubs are good places to begin the investigations. The analysis can also provide an indication of how efficient these hubs are in connecting rail/air with urban road traffic.

As seen from **Figure 4.36**, Beijing West Railway Station tends to attract an increasing number of taxis during the weekday mornings. In the early morning before 7.00AM, it seems that a large group of taxis are either berthing or resting in the vicinity of the station, with few other taxi movements (note that there may be some faster taxi movements with speeds greater than 25kmh, which have been filtered out in pre-processing). This is shown by the clusters which are almost all in red or orange (where taxis have speeds either below 2kmh or below 5kmh) in and around the station during 06:00:00-06:59:59AM. The taxi traffic starts to become faster moving from 07:30AM onwards, as there are more and more moving taxis of all speed ranges towards the station on the northwest links (green and yellow clusters during 07:30:00-07:59:59AM). The half hour after 8:00AM is, unsurprisingly, the most intensive for slow taxi movements in front of the Beijing West Station, as the red and orange clusters are in their maximum area coverages and spreading into the surrounding areas.



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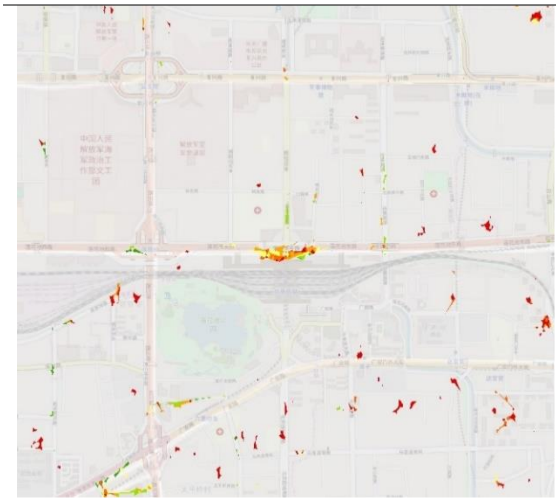
(b) 06:30:00 – 06:59:59 AM



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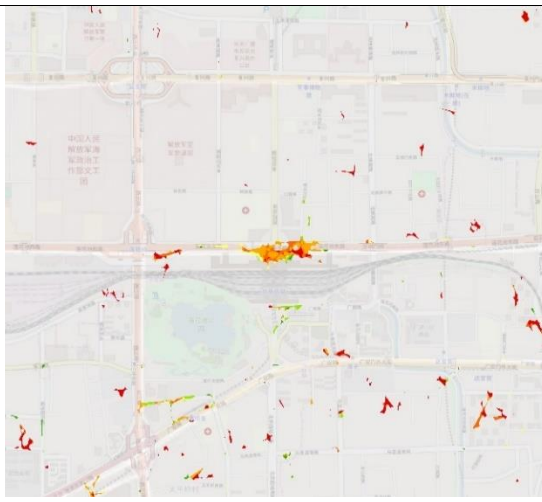

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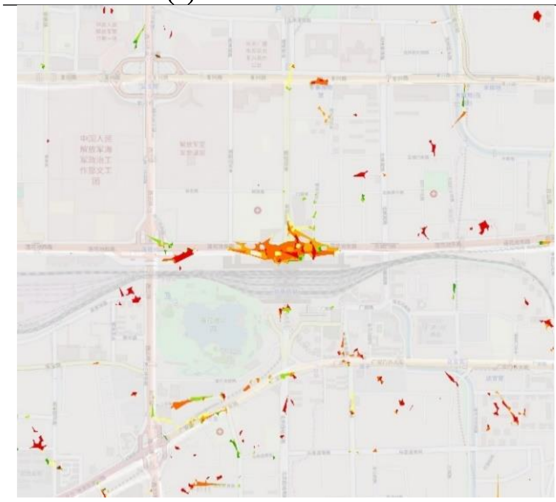
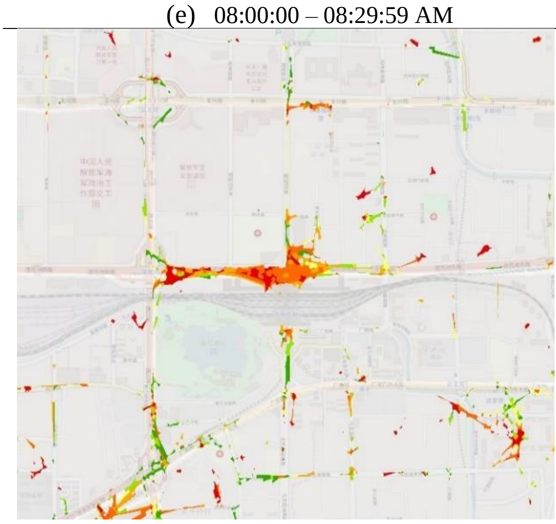
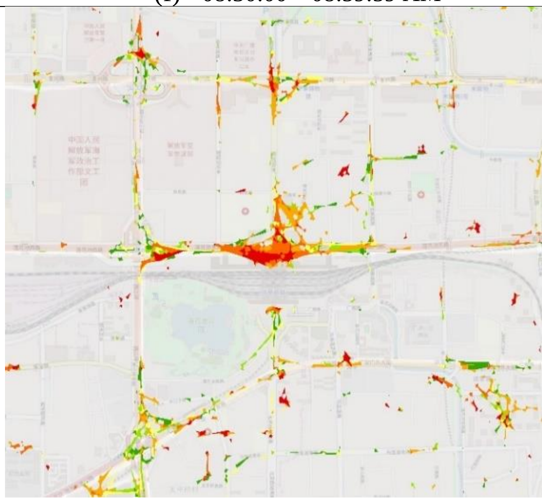


(e) 08:00:00 – 08:29:59 AM

(f) 08:30:00 – 08:59:59 AM



(g) 09:00:00 – 09:29:59 AM



(h) 09:30:00 – 09:59:59 AM

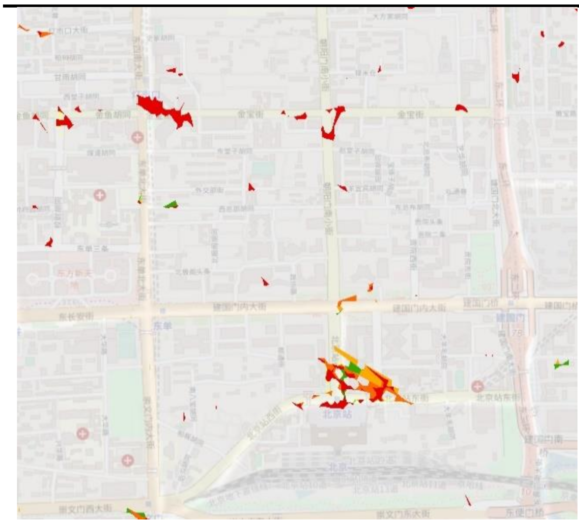
(i) 10:00:00 – 10:29:59 AM (j) 10:30:00 – 10:59:59 AM

Speed≤2kmh Speed≤5kmh Speed≤10kmh Speed≤15kmh Speed≤20kmh Speed≤25kmh

Figure 4.36. Identified Clusters near Beijing West Railway Station (Workday Group)

By contrast, clusters of the slow-moving taxis nearby Beijing Railway Station in the east of the city have far smaller spatial coverages (areas of clusters). While the slowest moving taxis are distributed far closer to the planned passenger loading and set down areas along the station exit plaza and thus remain less disruptive to the road space in the vicinity of the station (**Figure 4.37**; note that **Figure 4.37** and **Figure 4.36** are of the same scale). This confirms the experience reported by the taxi drivers in our field surveys that Beijing West Station is far more time consuming to access and load passengers than Beijing Railway Station. It is also commonly acknowledged by the Beijing planning and urban design circles that the street access layout at Beijing West Station performs poorly in terms of vehicle access, passenger loading and set down.

The cluster analysis here provides the first quantitative evidence for such anecdotal understanding. Since the detailed configurations of street microcirculation are peripheral to the main themes of this dissertation, we do not space here to pursue that further. However, the cluster analysis coupled with taxi trace data from e.g. before and after a redesign of the street access around a station could prove to be a new piece of quantitative evidence for monitoring design performance. In terms of the evolution of the cluster sizes, configurations and speed ranges over the time periods, the clusters in front of Beijing Railway Station appear to have a similar temporal profile to Beijing West Station. Note that the cluster analysis in **Figure 4.37** also picks up the traffic queues at the Chongwen Men junction to the west of the station, which builds up from 8AM and continue to grow till around 10.30AM as part of the city's rush hour.



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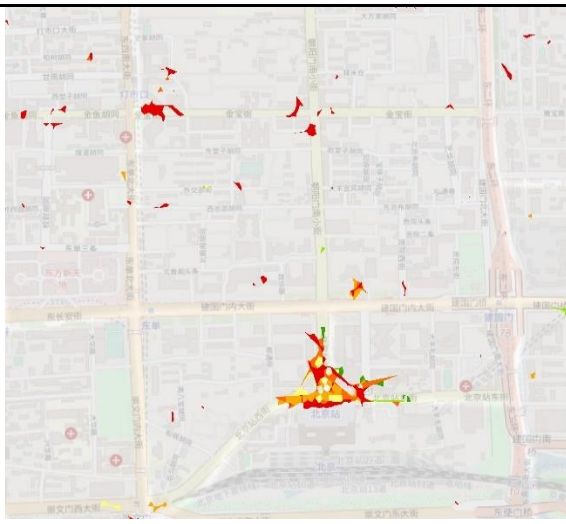

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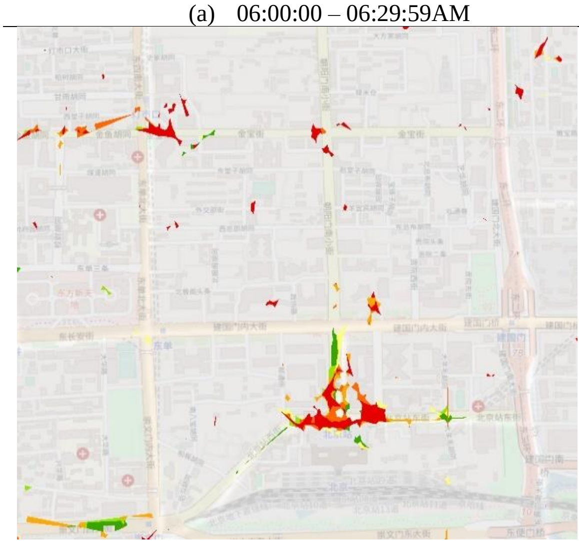

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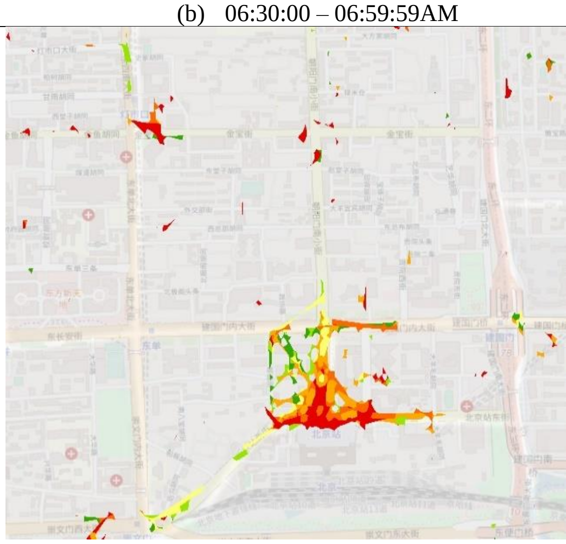

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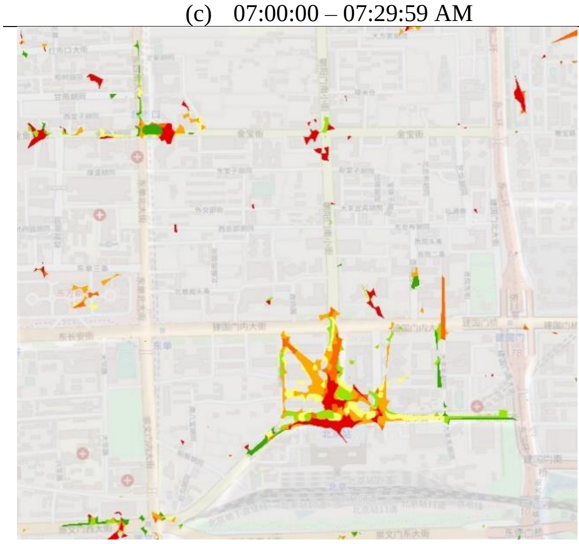

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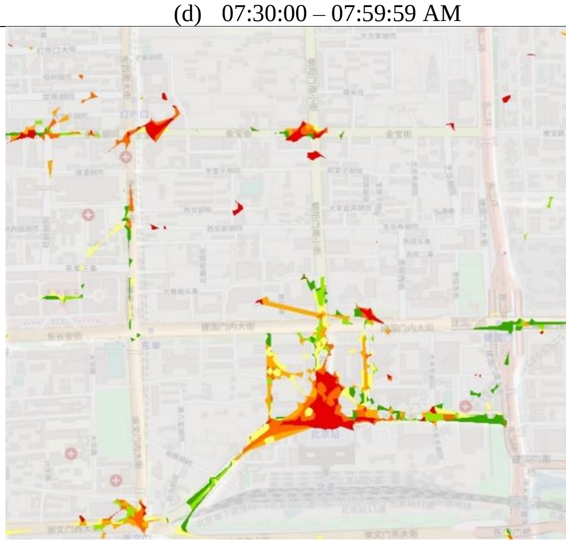
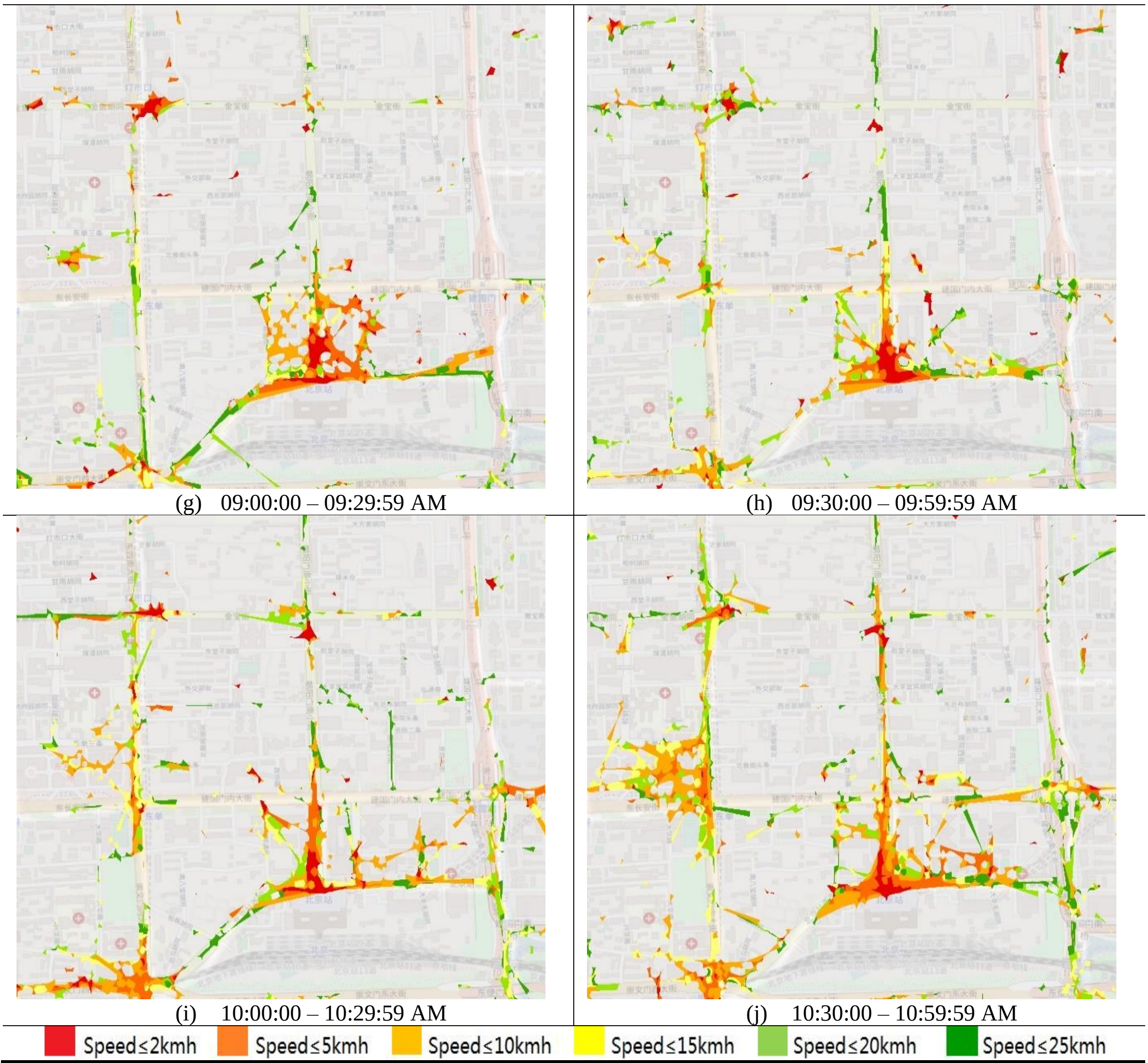


(f) 08:30:00 – 08:59:59 AM



(g) 09:00:00 – 09:29:59 AM

(h) 09:30:00 – 09:59:59 AM

(i) 10:00:00 – 10:29:59 AM

(j) 10:30:00 – 10:59:59 AM

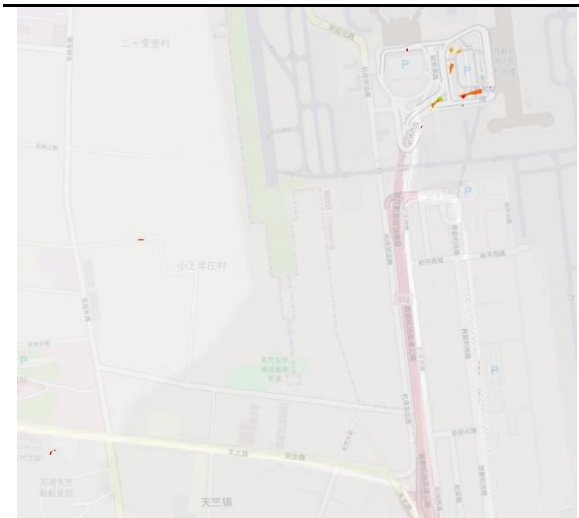
Figure 4.37. Identified Clusters near Beijing Railway Station (Workday Group)

The clustering pattern of taxi activities nearby the Capital Airport well reflects our experience of its Terminal 2 at that time (**Figure 4.38**). Before 6:30AM, there is no significant slow-moving clusters. This interprets that only a few taxis arrive to load a small number of arriving air passengers immediately. This pattern continues during 6:30-7:00AM, although a small cluster of quasi-stationary taxis starts to build up in a separate taxi parking facility to the west of Terminal 2. Based on our field survey (responses from the taxi drivers who could remember this facility at the time), this quasi-stationary cluster is formed by night-shift taxi drivers who arrive at the airport in the early morning and wish to take a break before loading passengers from Terminal 2.

From 7:00AM onwards, the slow-moving taxi clusters build up both at the terminal set down and pick up area and at the taxi park to the west. The latter now contains taxis that queue for picking up the air passengers. Since the connector road between the taxi park and Terminal 2 is uncongested and with few traffic lights, taxis would be able to move at a speed above 25kmh.

This is why only few clusters are visible in between, except a relatively slow build-up of clusters along the connector road in the later periods, particularly at the morning peak half hour 9:30-10:00AM.

The Terminal 2 clusters show unambiguously that with a concentration of the taxi trace data and suitably frequent taxi signals relative to vehicle speeds, it is possible to detect and quantify traffic patterns in a precise way.



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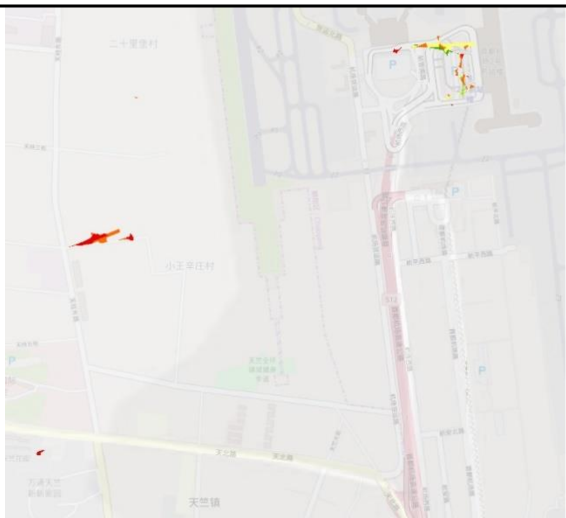

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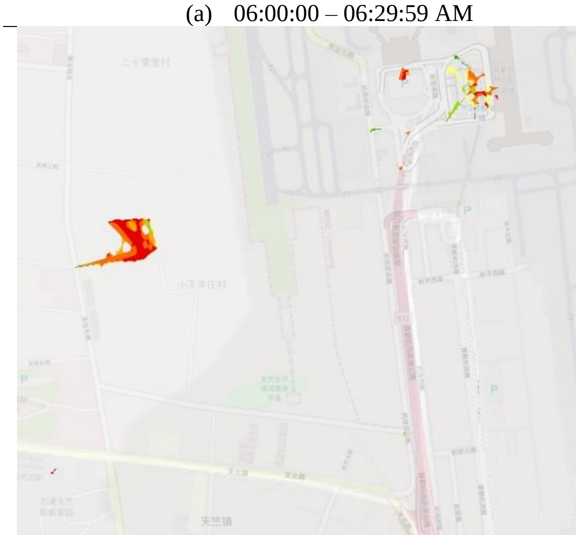

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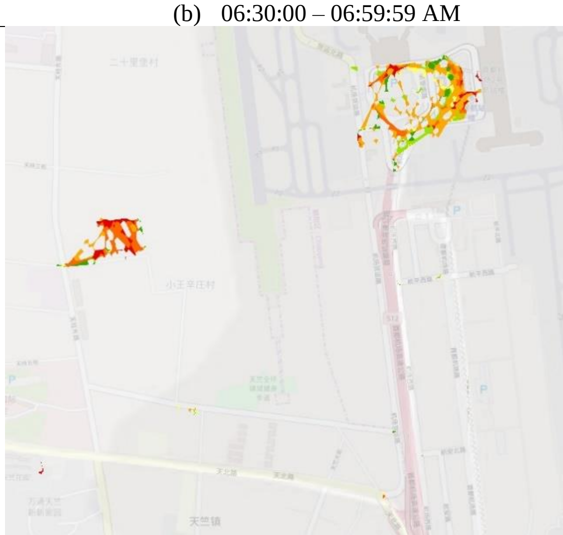

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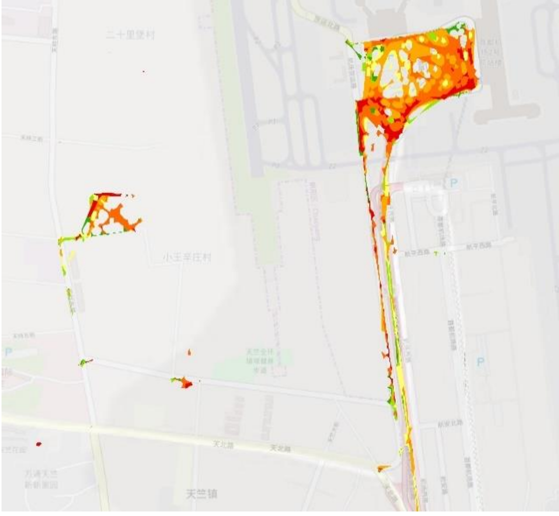
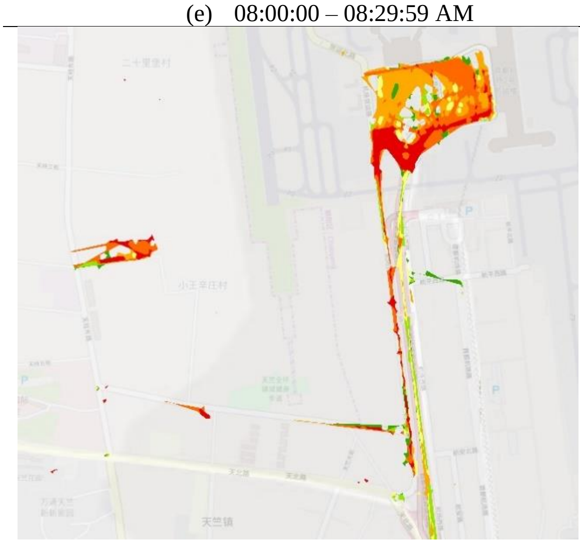
(e) 08:00:00 – 08:29:59 AM



(f) 08:30:00 – 08:59:59 AM



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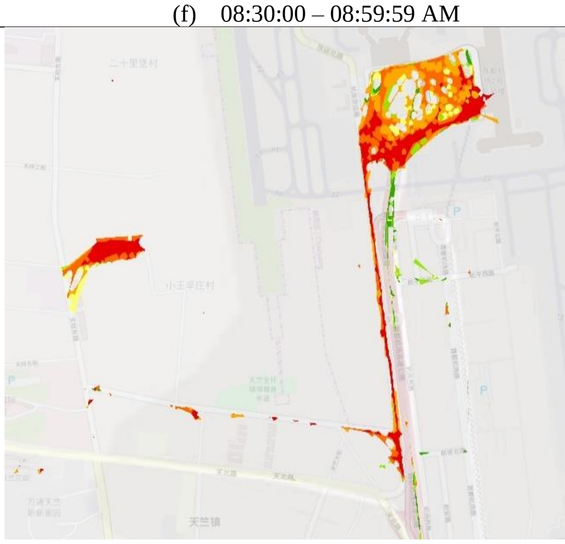


(h) 09:30:00 – 09:59:59 AM

(i) 10:00:00 – 10:29:59 AM

(j) 10:30:00 – 10:59:59 AM

Speed≤2kmh Speed≤5kmh Speed≤10kmh Speed≤15kmh Speed≤20kmh Speed≤25kmh

Figure 4.38. Identified Clusters near Capital Airport (Workday Group)

- ***Urban road junctions***

Building on the analyses of the transport hubs, we further investigate the clusters nearby four well-known heavily congested road junctions in central Beijing, which are Xi Zhi Men, Ji Shui Tan/De Sheng Men, Guo Mao (CBD), and Chong Wen Men (**Figure 4.39**). As shown in **Figure 4.40**, **Figure 4.41**, **Figure 4.42** and **Figure 4.43**, the resulting clusters confirm that all these juntions experience severe level of congestion. It is worth noting that we assume taxi speed is indicative of the general traffic speed, since taxis do not move any faster than other vehicles under heavy congestion when traffic speeds are below 25km.

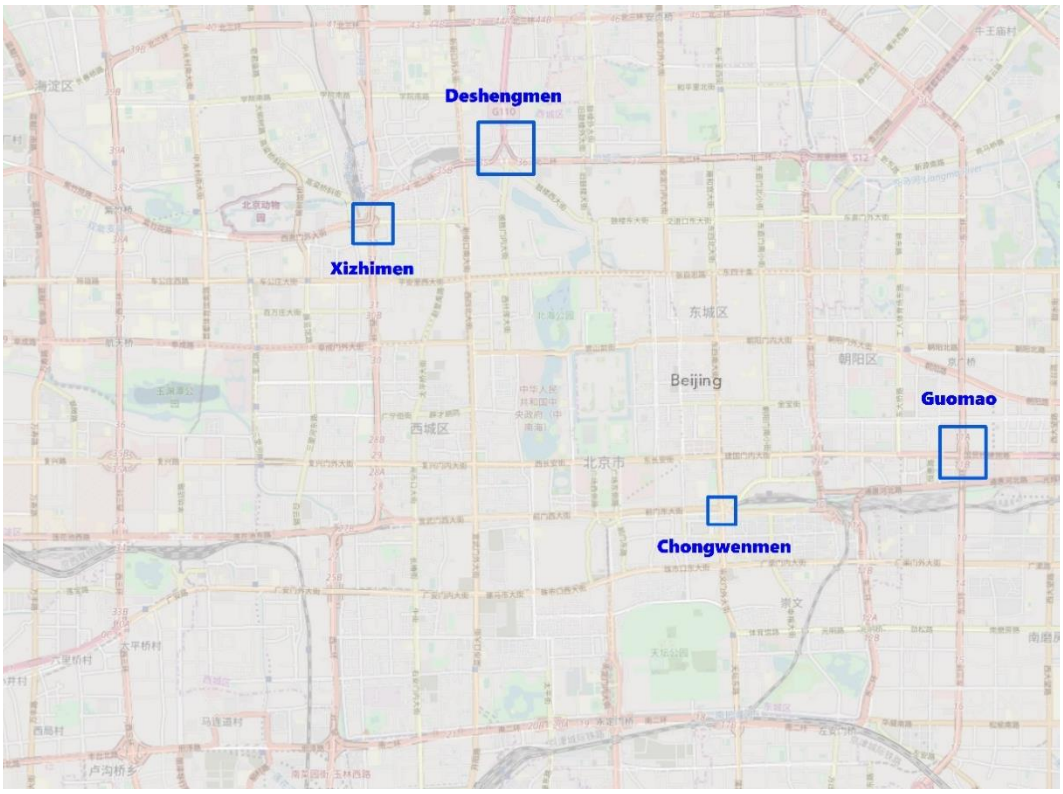
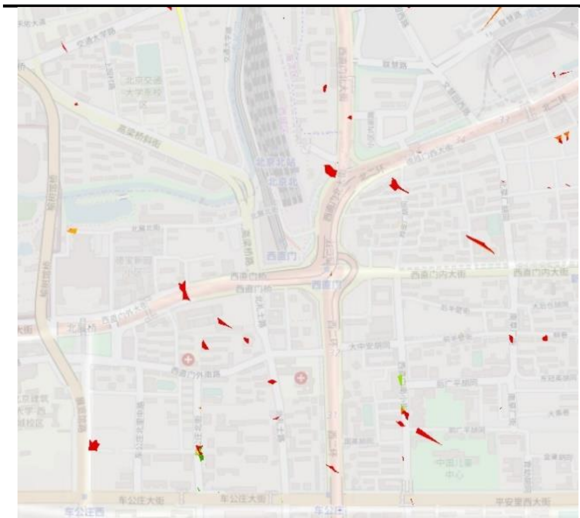


Figure 4.39. Selected urban road junctions for taxi hotspot investigation

However, the cluster analysis here also reveals a serious shortcoming of the application of DBSCAN cluster analysis for taxi trace data in the context of road junctions: because the number of taxis in the dataset is relatively small for the commonly recognised morning peak period (i.e. 6:30-9:30AM), and the taxi numbers do not build up much untill the latter part of that period, the slow moving taxi clusters themselves can only be clearly identified after 9:00AM around the road junctions. This means that cluster analysis of slow moving taxis alone is not sufficient for identifying more general road congestion patterns. This is an issue that we will now turn to address in the next section regarding congested road link speeds for the morning peak period.



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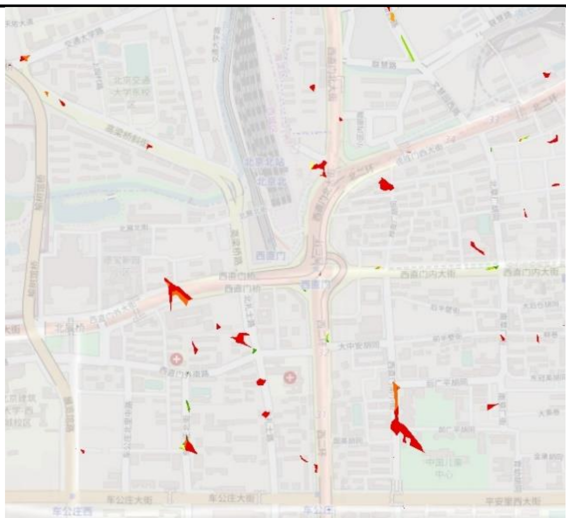

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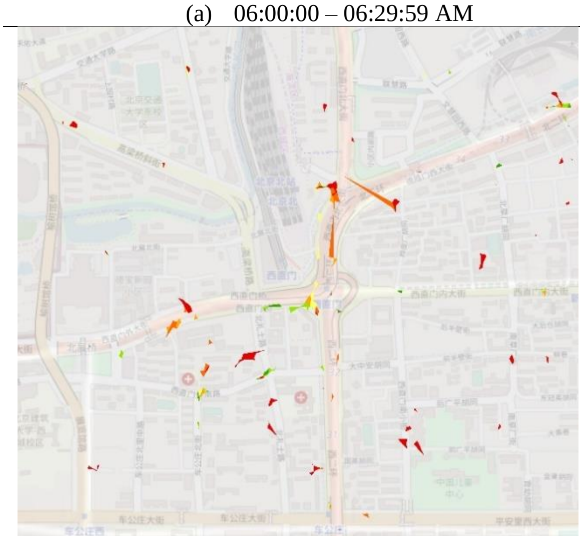
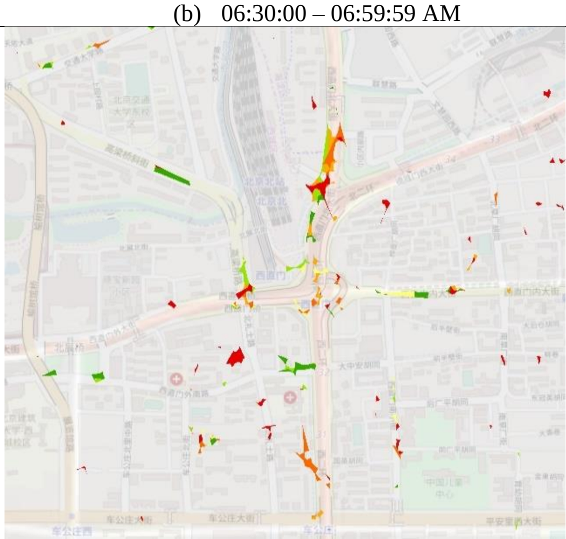


(c) 07:00:00 – 07:29:59 AM



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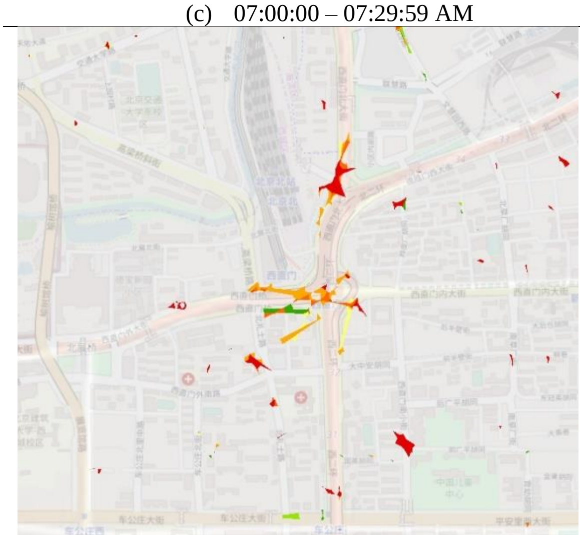
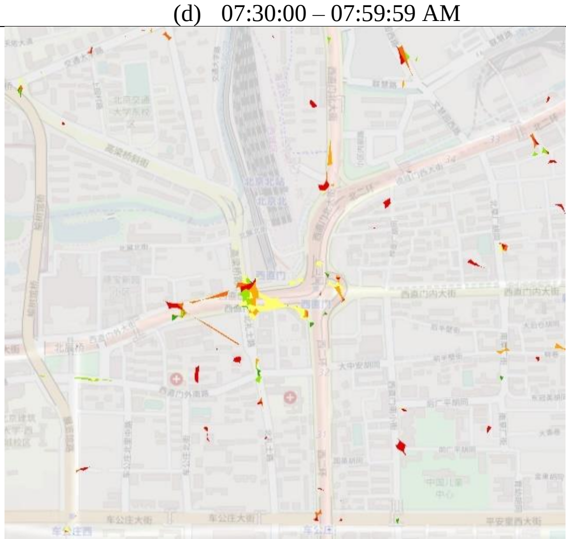


(e) 08:00:00 – 08:29:59 AM



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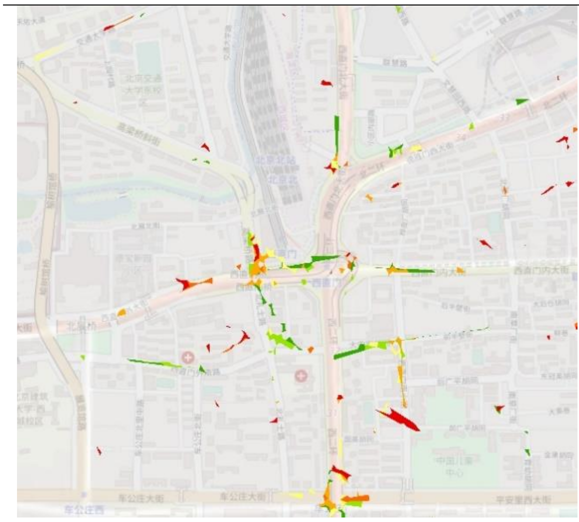

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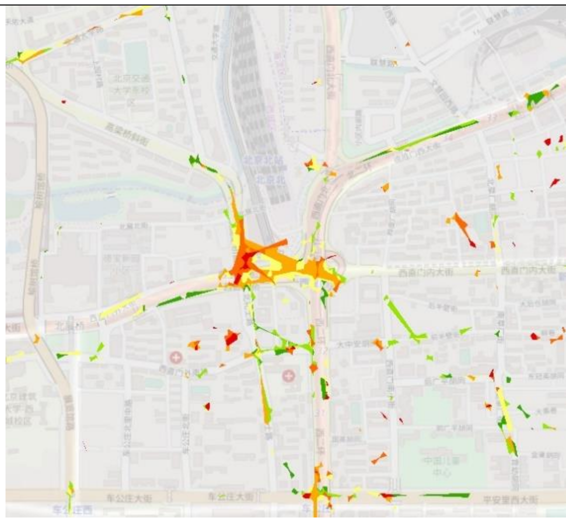

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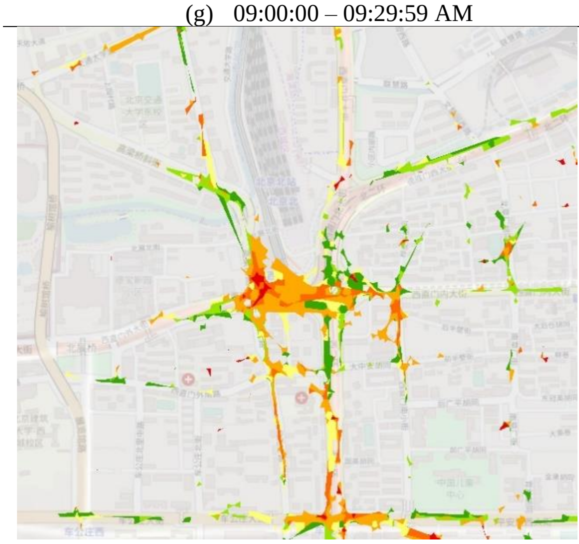

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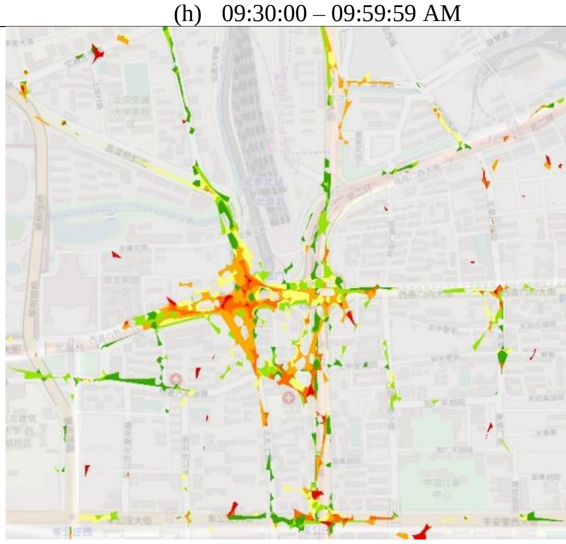
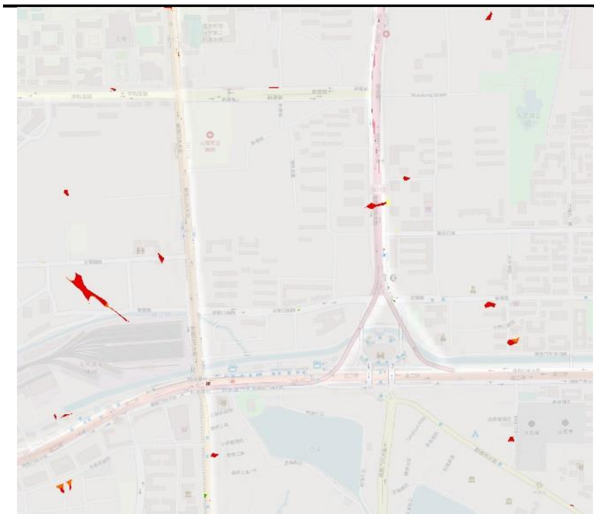


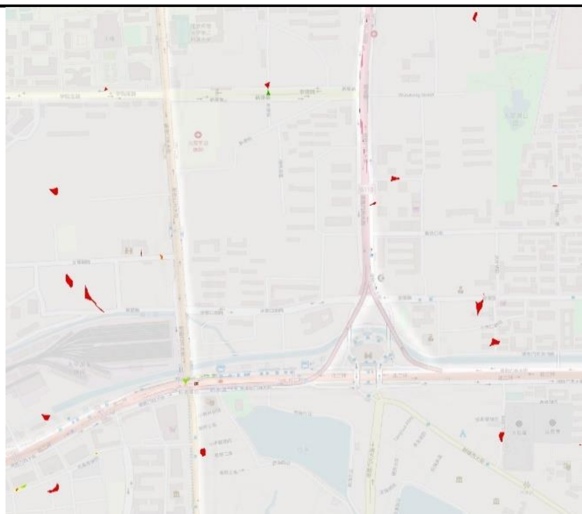
(j) 10:30:00 – 10:59:59 AM

Speed≤2kmh Speed≤5kmh Speed≤10kmh Speed≤15kmh Speed≤20kmh Speed≤25kmh

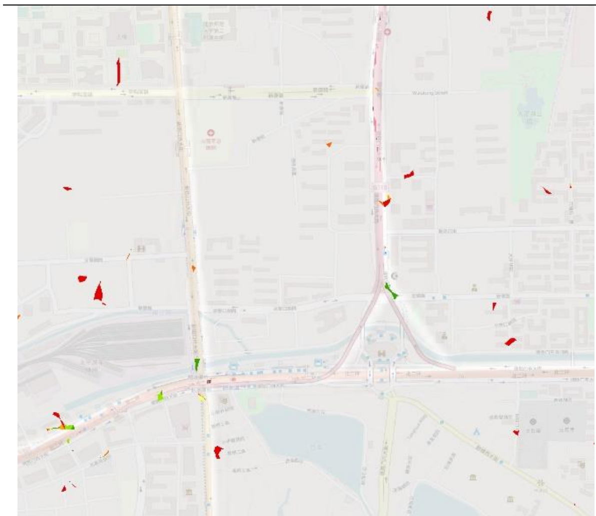
Figure 4.40. Identified Clusters near Xizhimen (Workday Group)



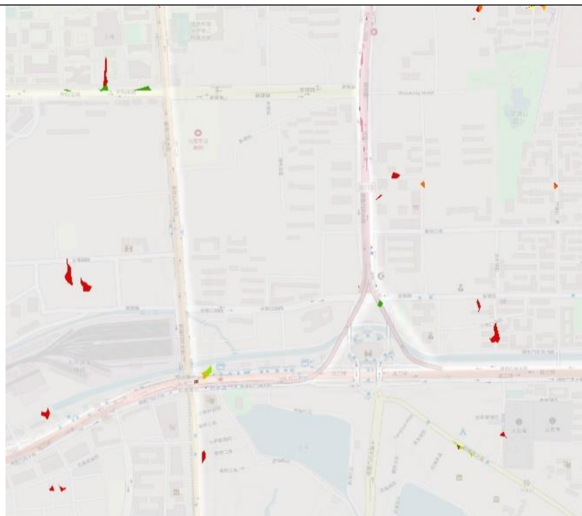
(a) 06:00:00 – 06:29:59 AM



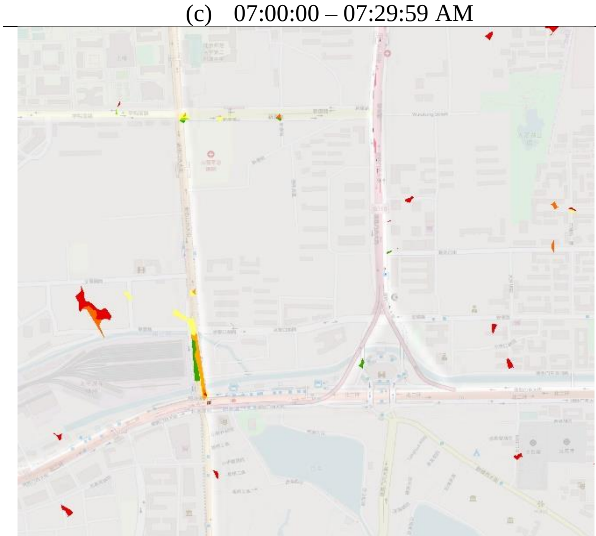
(b) 06:30:00 – 06:59:59 AM



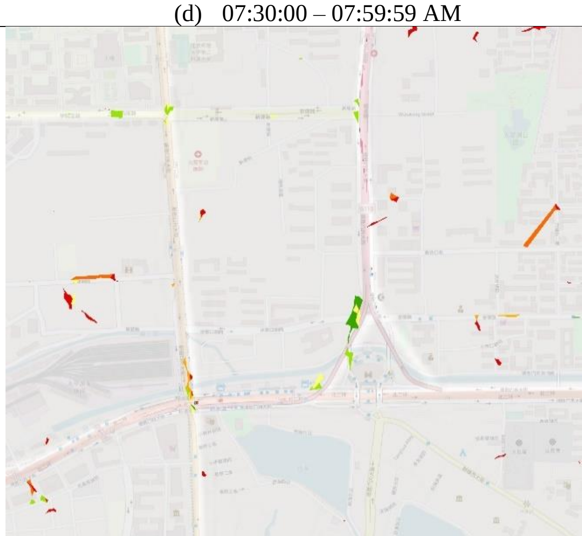
(c) 07:00:00 – 07:29:59 AM



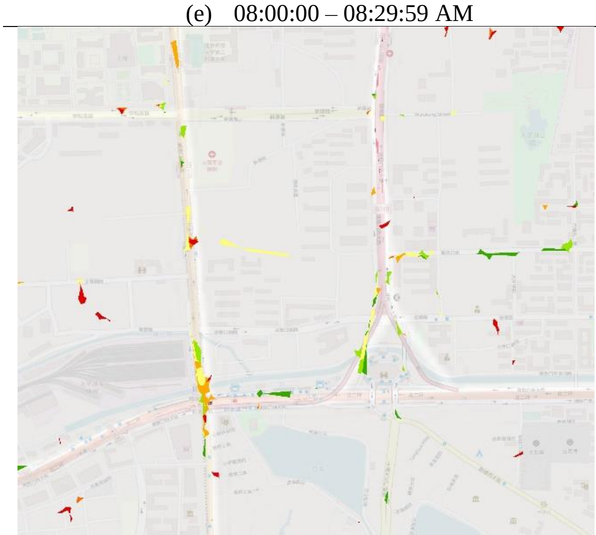
(d) 07:30:00 – 07:59:59 AM



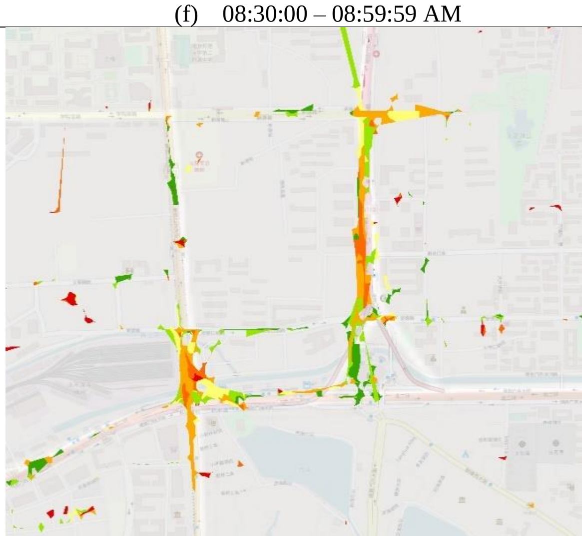
(e) 08:00:00 – 08:29:59 AM



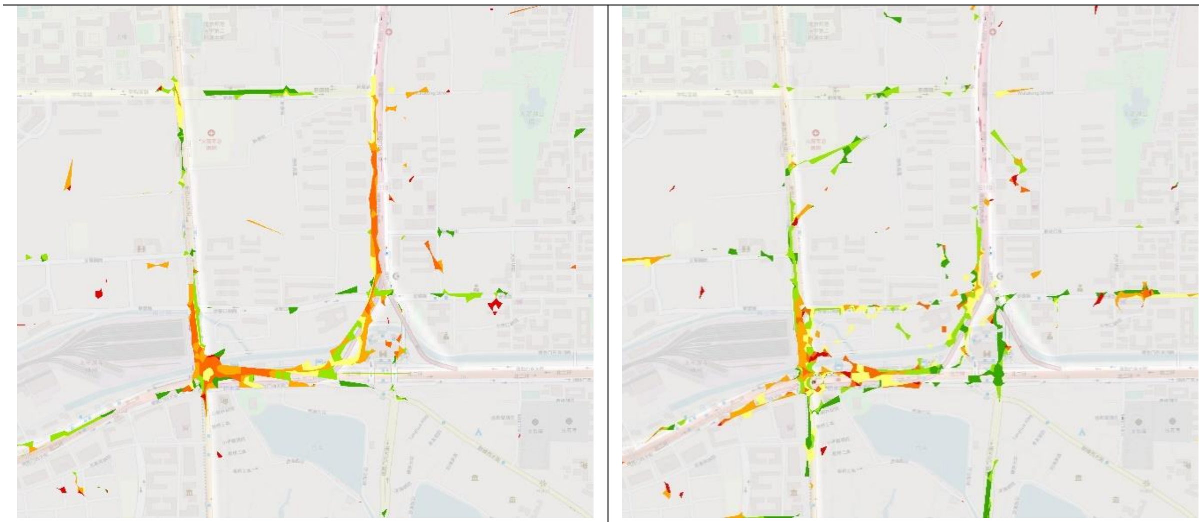
(f) 08:30:00 – 08:59:59 AM



(g) 09:00:00 – 09:29:59 AM



(h) 09:30:00 – 09:59:59 AM

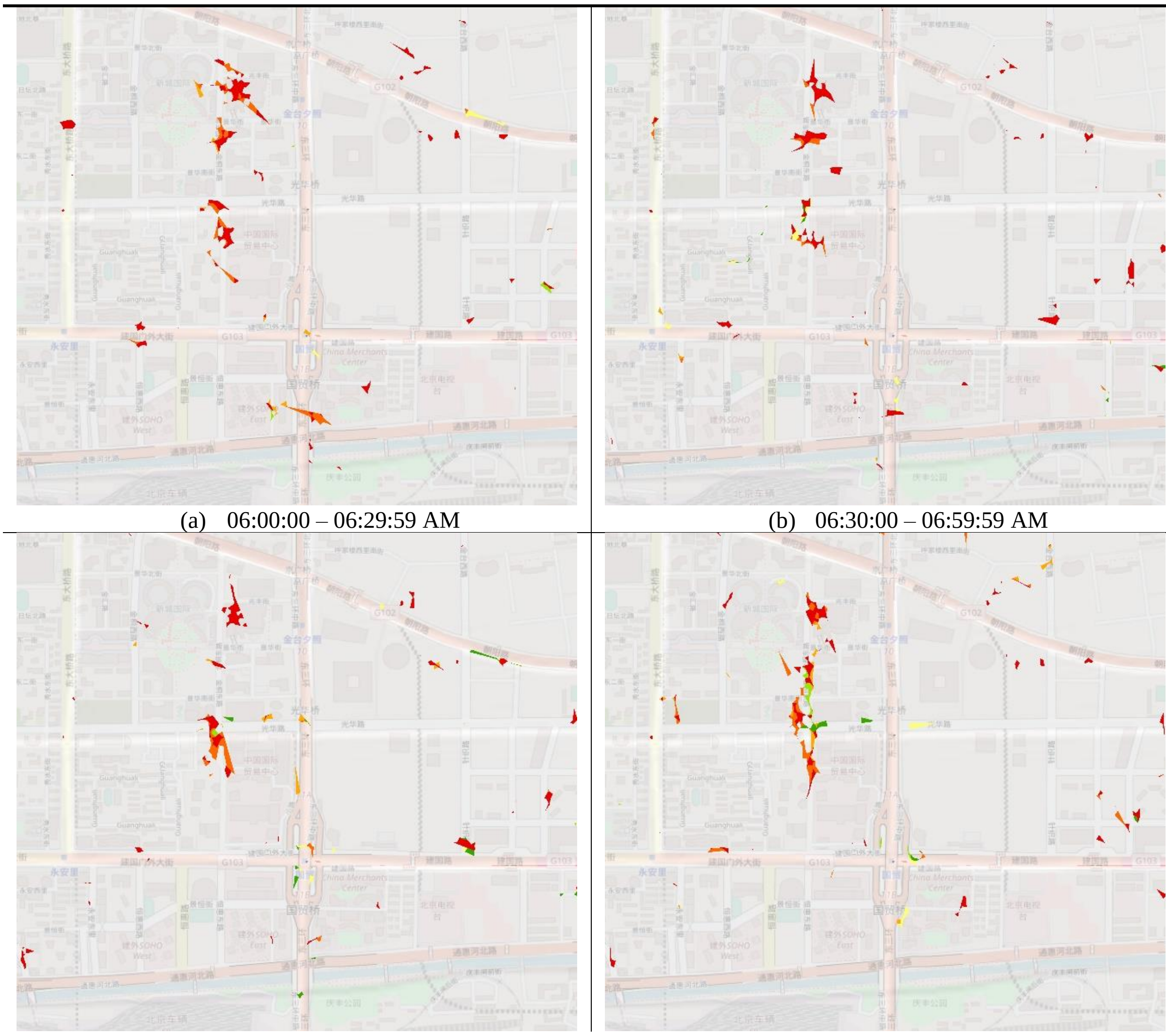


(i) 10:00:00 – 10:29:59 AM

(j) 10:30:00 – 10:59:59 AM

Speed≤2kmh Speed≤5kmh Speed≤10kmh Speed≤15kmh Speed≤20kmh Speed≤25kmh

Figure 4.41. Identified Clusters near Jishuitan and Desheng Men (Workday Group)



(a) 06:00:00 – 06:29:59 AM

(b) 06:30:00 – 06:59:59 AM

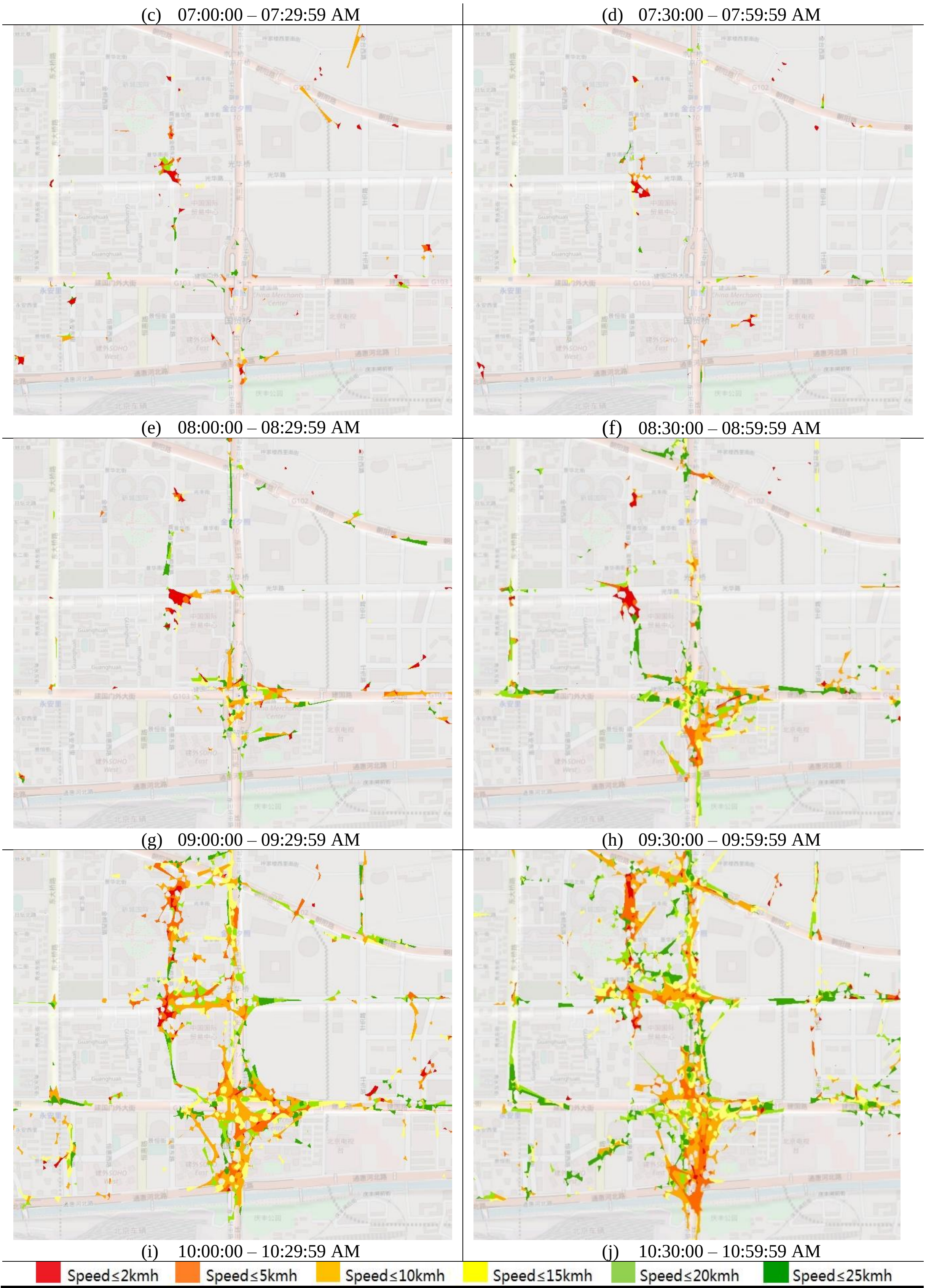
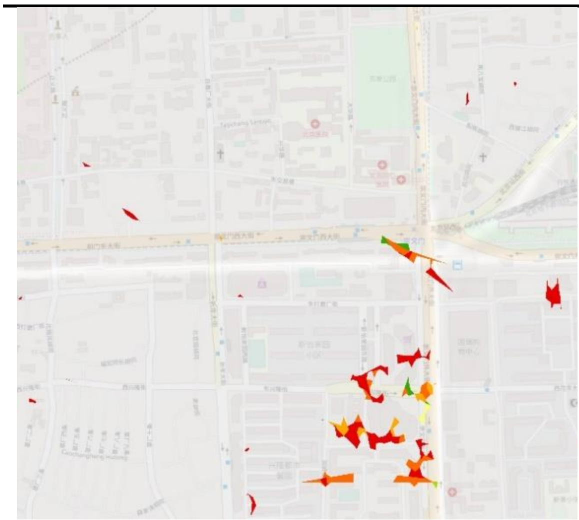
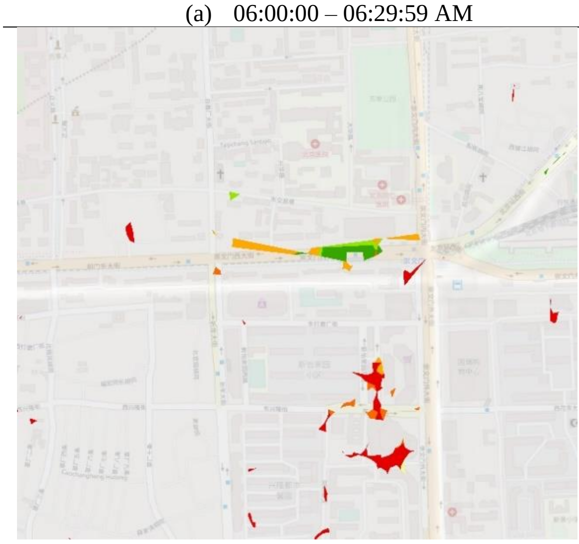


Figure 4.42. Identified Clusters near Guo Mao CBD (Workday Group)

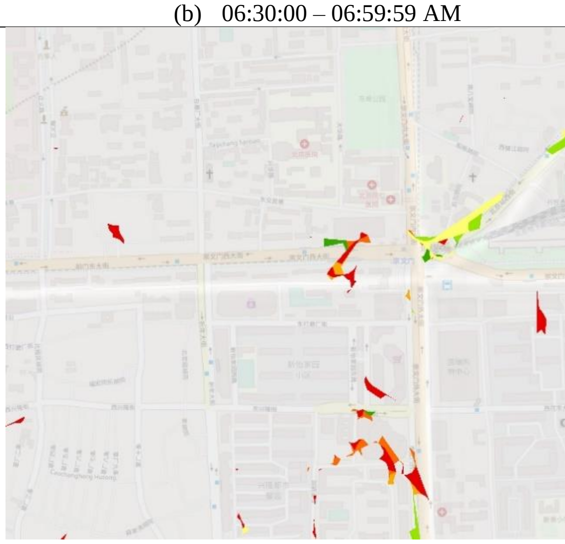


(a) 06:00:00 – 06:29:59 AM

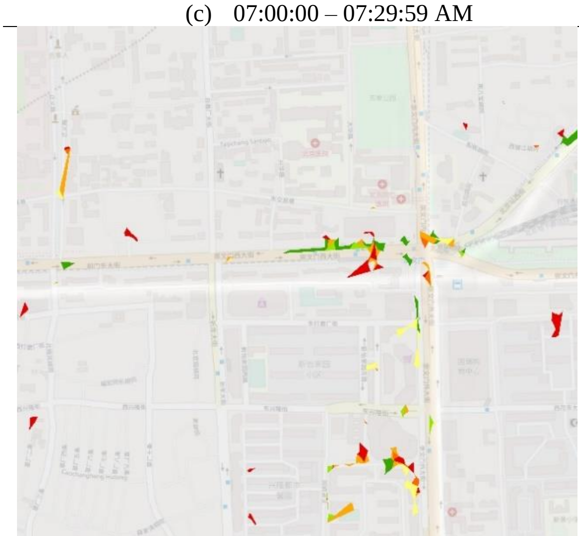
(b) 06:30:00 – 06:59:59 AM



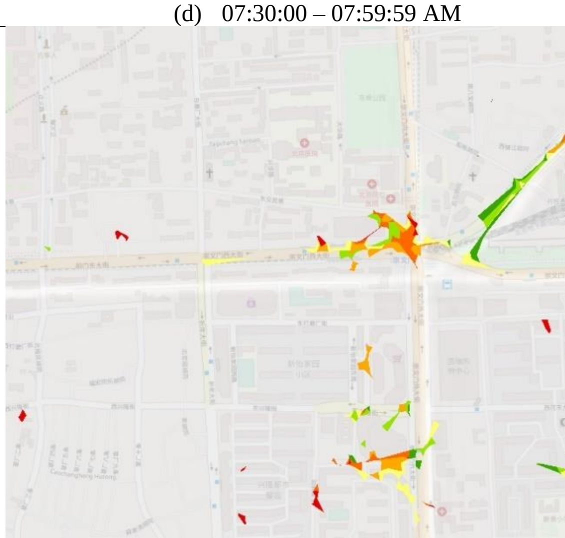
(c) 07:00:00 – 07:29:59 AM



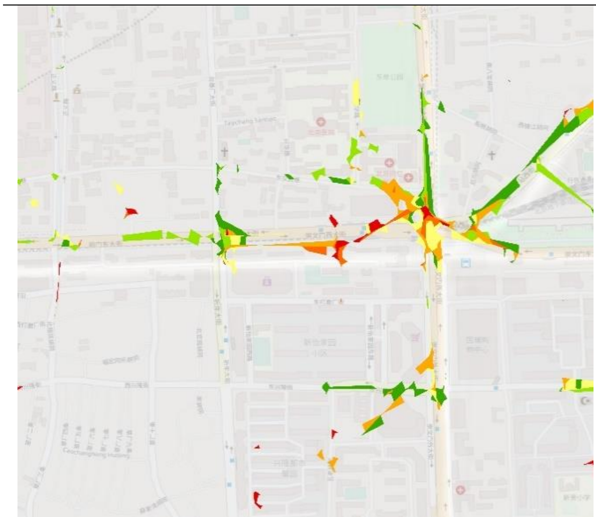
(d) 07:30:00 – 07:59:59 AM



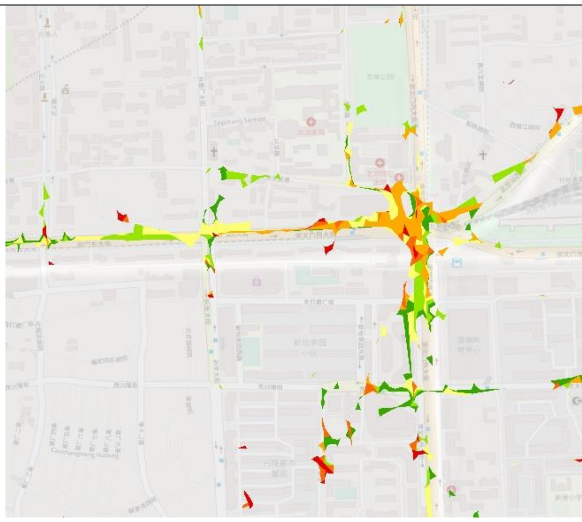
(e) 08:00:00 – 08:29:59 AM



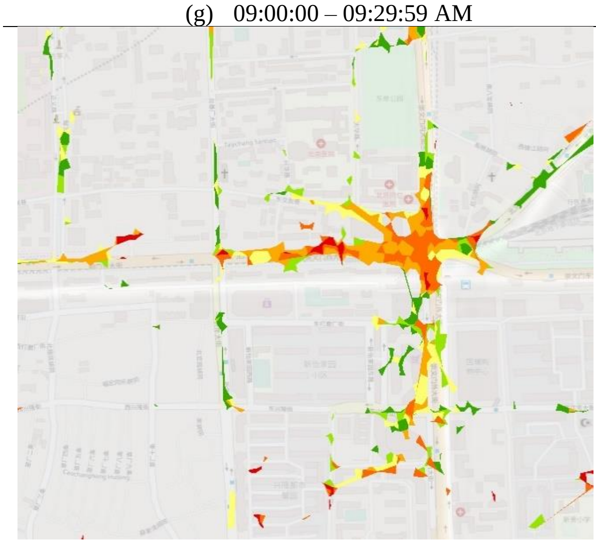
(f) 08:30:00 – 08:59:59 AM



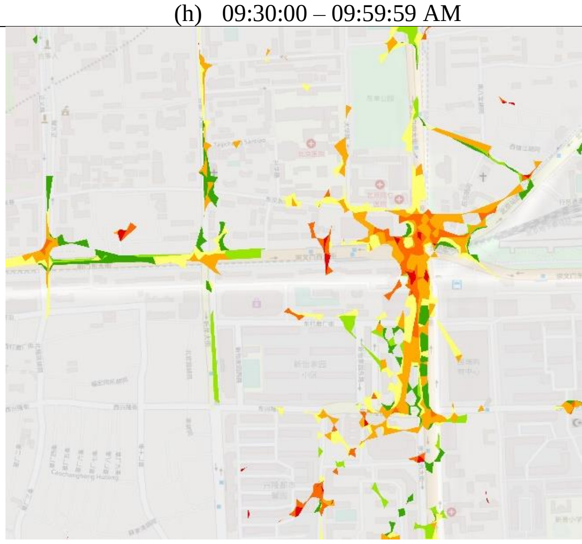
(g) 09:00:00 – 09:29:59 AM



(h) 09:30:00 – 09:59:59 AM



(i) 10:00:00 – 10:29:59 AM



(j) 10:30:00 – 10:59:59 AM

Speed≤2kmh Speed≤5kmh Speed≤10kmh Speed≤15kmh Speed≤20kmh Speed≤25kmh

Figure 4.43. Identified Clusters near Chongwen Men (Workday Group)

4.6. Estimating Congested Road Traffic Speeds from Taxi Traces

4.6.1. Congested Link Speed for Beijing (within 5th Ring Road)

In cities that have significant peak period congestions, observed congested link speeds (which are required for Base Year model calibration) are usually very costly and difficult to establish. Such congested speeds should ideally cover all the urban areas where considerable congestion occurs. Traditionally, in transport modelling, such congested speeds could be estimated through e.g. observed traffic flows (the volume of traffic) on each road link from survey data, relative to the road links' throughput capacities, and then the model could be validated in some way through limited road speed observations on key traffic links. However, such methods are subject to a few uncertainties in the data, and in the assumed speed-flow curves which simulates the slowdown of traffic. In addition, they usually do not adequately take account of congestion times that arise from different traffic queuing behaviour at traffic lights and road merging points. In this section, we develop, test and validate a new method that derives congested road speeds including junction delays using the Beijing taxi GPS traces, which have been explored above.

From the analysis in **Section 4.5** above, it is clear that purely relying on the traces from the subset of slow-moving taxis would not be sufficient in covering the urban road network except at the very congested junctions and main taxi pick up/set down sites. There is, however, a major challenge in making use of the faster moving taxis. This is because that the sampling rate of the GPS data is infrequent, and the average sampling time interval is about 219 seconds over AM periods in the workdays (**Table 4.18**). Assume that a vehicle moving with a 20kmh speed, then in 219 seconds, it can travel over 1,200 metres between two consequential GPS data points on average. As this average travelling distance between pairs of consequential data points is much longer than the average link length (335.2 meters) of the modelled road network, a research question emerges in how to estimate link traffic delays and driving speeds over the modelled network.

Table 4.18. Average sampling interval (AM Periods, Workdays)

Date	Counts of Records		Sampling Times (s)	
(6-11am)	Total	Filtered	Mean	Median
4th Feb 2008	562,612	115,018	206.10	221
5th Feb 2008	509,690	90,977	219.61	251
6th Feb 2008	422,795	46,614	231.97	300
Total	1,495,097	252,609	219.23	/

To overcome this issue which may be common among vehicle GPS trace data from many cities, we apply the map-matching and path inference method which can exploit relatively low frequency GPS signal samples (for the development of the method, see **Chapter 3**).

In order to minimise the uncertainty and enhance the accuracy in the map-matching and path-inference processes, a filtering process is first applied to remove the unfit taxi GPS trajectories, based on their point-to-point sampling interval length and speed, along with proximity to the network itself. This filtering process consists of three steps as follows:

(1) Select taxi traces which are entirely within the Beijing Fifth Ring Road: As the GPS data points outside the Fifth Ring is relatively sparse, they will be removed at this step. For the estimation of congested speeds outside the fifth ring road, a simpler, broader brush method is used (see below).

(2) Exclude taxi traces with a crow-fly link length less than one hundred meters: This is because the GPS signals have a considerable margin of error regarding the true signal footprint locations. Although it is not possible to know the precise extents of location errors implied by the numerous taxi GPS devices, our visual checks of the apparent outliers suggest that the range of errors tend to be within ±25 metres. Nevertheless, an error margin of 25 metres could significantly change the implied speeds of the short trace links such as those under 100 metres.

(3) Remove trajectories that indicate a point-to-point straight-line speed greater than 120 km/h: Since this is the speed limit for the expressways in China and no taxi speeds inside the Fifth Ring Road should reach anything close to this. Such data points could be generated in machine error or caused by the assumption of crow-flies between two signal footprints where the taxi in question goes through a circuitous route.

We then specify the tolerances b_{R^m} for each road link R^m, based on the equation which has been discussed in Chapter 3 (see **Equation 3.10** in **Chapter 3**):

$$b_{R^m} = (d_l\left(f(R^m)\right)x\, n_l(R^m)) + (d_s\left(f(R^m)\right) x\, n_s(R^m)) + d_u\left(f(R^m)\right) \qquad \textbf{Equation 3.10}$$

where,

b_{R^m} is the buffer distance of link R^m;

$f(R^m)$ is the link type classification function (i.e. it returns the link type of R^m);

$d_l\left(f(R^m)\right)$ is the typical lane width for link type $f(R^m)$;

$n_l(R^m)$ is the number of lanes of link R^m;

$d_s\left(f(R^m)\right)$ is the typical width of central separation band for $f(R^m)$;

$n_s(R^m)$ is the number of central separations of link R^m; and,

$d_u(f(R^m))$ is the typical width of the utilities buffer on the sides of link type $f(R^m)$.

In essence, along a specific road link, its tolerance width (buffer) aims to represent the breadth of the possible range where the GPS signal points could possibly fall on. **Table 4.19** specifies the parameter values for all the relevant road link types inside the fifth ring road.

Table 4.19. Network proximity tolerances

Road Type	**Lane Width /m**	**Number of Lanes**	**Utilities Width /m**	**Total tolerance width /m**
$f(R^m)$	$d_l(f(R^m))$	$n_s(R^m)$	$d_u(f(R^m))$	b_{R^m}
Jing Ha (G1) Expressway	3.75	4	9.75	24.75
Jing Hu (G2) Expressway	3.75	4	9.75	24.75
Jing Shi (G4) Expressway	3.75	3	9.5	20.75
Jing Zang (G6) Expressway	3.75	3	9.5	20.75
Beijing Airport (S12) Expressway	3.75	4	9.75	24.75
Beijing Airport North Line (S28) Expressway	3.75	4	9.75	24.75
Jing Jin (S30) Expressway	3.75	4	9.75	24.75
Jing Ping (S32) Expressway	3.75	3	9.5	20.75
Airport 2nd Expressway (S51)	3.75	4	9.75	24.75
Jing Jin (S1) Expressway	3.75	4	9.75	24.75
Jing Tong Expressway (G102)	3.75	4	9.75	24.75
Jing Kai Expressway (G106, part of G45)	3.75	4	9.75	24.75
Jing Cheng (S11, part of G45)) Expressway	3.75	3	9.5	20.75
Beijing second ring road	3.75	3.5	6.625	19.75
Beijing third ring road	3.75	4	6.75	21.75
Beijing fourth ring road	3.75	4	6.75	21.75
Beijing fifth ring road	3.75	3	6.5	17.75
Beijing sixth ring road	3.75	2	6.25	13.75
First class road within second ring road	3.75	6	5.25	27.75
First class road between 2nd and 3rd ring road	3.75	4	4.75	19.75
First class road between 3rd and 4th ring road	3.75	4	4.75	19.75
First class road between 4th and 5th ring road	3.75	4	4.75	19.75
First class road between 5th and 6th ring road	3.75	4	4.75	19.75
Second class road within second ring road	3.5	4	4.25	18.25
Second class road between 2nd and 3rd ring road	3.5	4	4.25	18.25
Second class road between 3rd and 4th ring road	3.5	4	4.25	18.25
Second class road between 4th and 5th ring road	3.5	4	4.25	18.25
Second class road between 5th and 6th ring road	3.5	4	4.25	18.25
Third class road within second ring road	3.5	3	3	13.5
Third class road between 2nd and 3rd ring road	3.5	3	3	13.5
Third class road between 3rd and 4th ring road	3.5	3	3	13.5
Third class road between 4th and 5th ring road	3.5	3	3	13.5
Third class road between 5th and 6th ring road	3.5	3	3	13.5
Fourth class road within second ring road	3	2	2.75	8.75
Fourth class road between 2nd and 3rd ring road	3	2	2.75	8.75
Fourth class road between 3rd and 4th ring road	3	2	2.75	8.75
Fourth class road between 4th and 5th ring road	3	2	2.75	8.75
Fourth class road between 5th and 6th ring road	3	2	2.75	8.75
Infill Links	3	2	2.20	8.20

As discussed in **Section 4.5.1**, significant limitation in the dataset is the absence of the taxi status information, i.e. it is not known whether a taxi is waiting for a passenger, travelling with a passenger, travelling without a passenger or parked. This does present a challenge for us, because a taxi trace link with an observed zero speed (i.e. with the start and end signal footprints coinciding) could imply either parking/waiting or standing still in congested traffic. If the taxi is parked or waiting for passengers, then the trace link in question should not be included in the estimation of speed on the network. If the taxi is in congested traffic, then it should be included. Here in view of the relatively infrequent signals with a median sampling frequency of 219 seconds, we assume that taxis with zero speed are either for waiting or parked. We then remove all such trace links from the analysis. This leaves open the possibility of slightly biasing the estimated speeds upwards and we return to this issue below when considering validation.

As seen in **Table 4.20**, there are much less data counts in Tuesday and Wednesday compared to Monday; this statistics has been confirmed to be correct – one would expect that as the Chinese New Year drew nearer fewer people would be going to work etc, so the reason behind the reduction in data point is the limitation of the source sample data itself.

Table 4.20. Data used for congested road link speeds (AM periods, workdays)

	Monday 4 February	**Tuesday 5 February**	**Wednesday 6 February**
Trajectories processed (after cleaning process)	115,018	90,977	46,614
Number of modelled road links (within 5th ring road)	47,262	47,262	47,262
Number of routes generated	110,414	20,113	11,483
Number of speed values	1,203,646	209,941	122,151
Links with speed values	27,260	20,157	17,326
Average route length	3.3 km	3.0km	2.9 km

Following the methodology in mapping the signal footprints onto the road network (developed in **Chapter 3**), we identify the most possible routes (on the modelled road network) for each of the qualified crow-fly GPS trace links, and through an iterative process attribute speeds onto each modelled road link.

As a sense check of the overall patterns of the resulting average speeds, **Figure 4.44** shows the average estimated link speed by road link type and location. As expected, average link speeds tend to increase from the centre of Beijing outwards for comparable link types. Also, the lower the road grade, the lower the average speed within an area.

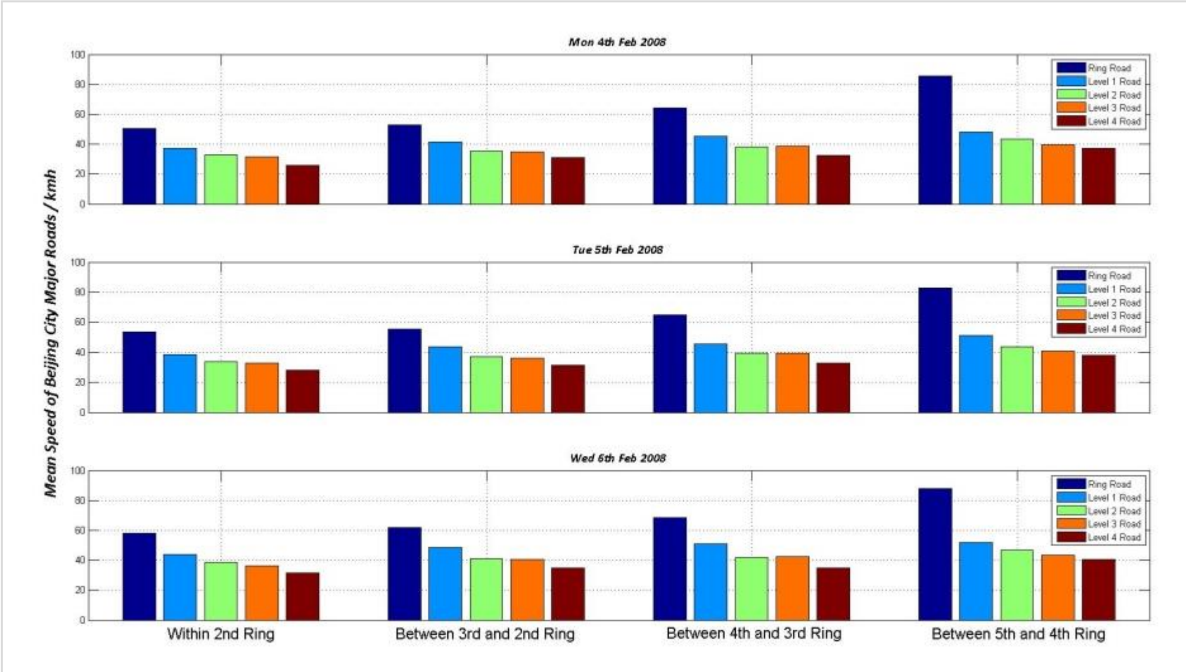


Figure 4.44. Average estimated link speeds by link type (6-11AM, workdays)

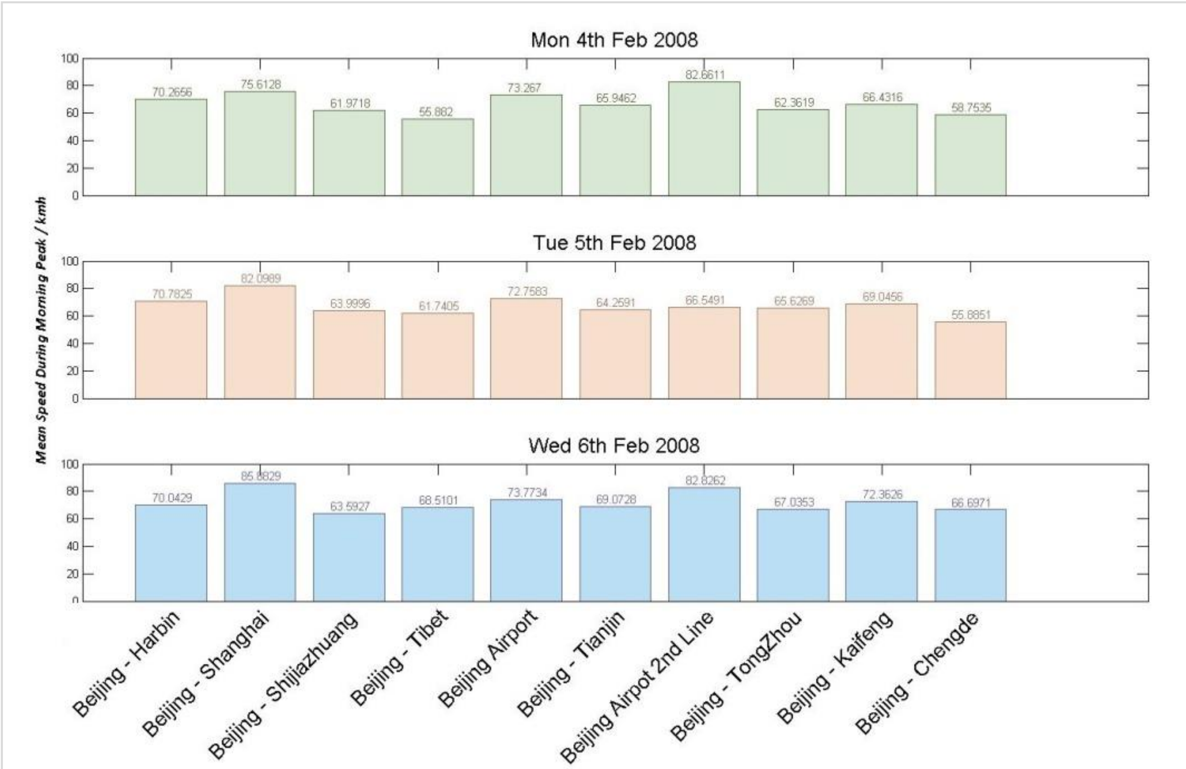


Figure 4.45. Estimated average link speeds on ten expressways in Beijing (6-11AM, workdays)

In **Figure 4.45**, we examine the average estimated link speeds on major expressways in Beijing, for the morning traffic period (6-11AM) on the three working days. Again, the patterns are in line with the expected. The expressway speeds are relatively high, and in general, the closer it is to the Chinese New Year, the higher the traffic speeds as long-distance travel for the Chinese New Year falls in trip volume.

The resulting link speeds can be further assessed statistically as follows.

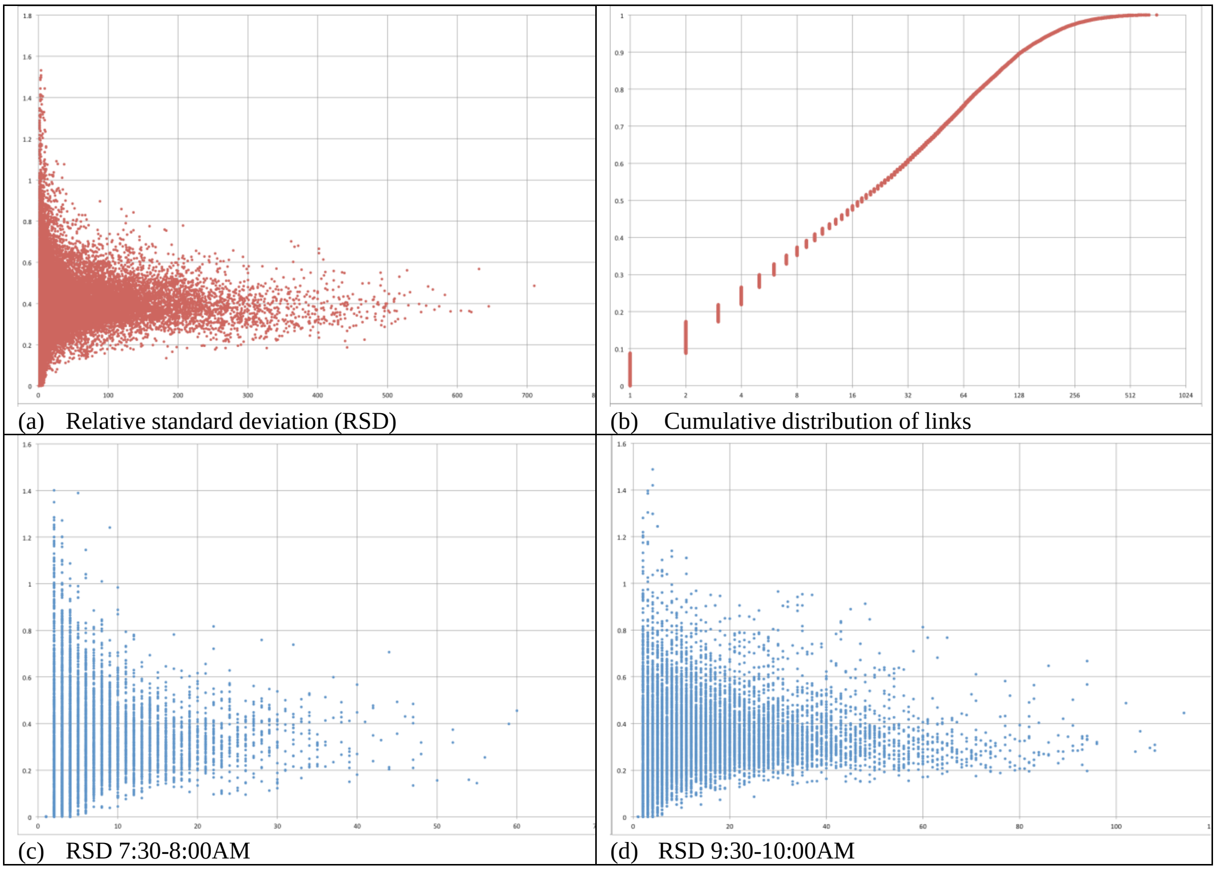
Building on the equations in **Chapter 3**, this statistical analysis investigates whether the average congested link speed $speed_k(R^m)$ for link R^m is statistically significant based on the distribution of separate link time attributions $t_k^{P1 \to P^2}(R^m)$ from all relevant link speed estimations, i.e. we assess how the average estimated link speed $speed_k(R^m)$ is related to the speeds implied by attributions of congested travel times $t_k^{P1 \to P^2}(R^m)$ from any trace link consists of GPS point pairs $[P^1, P^2]$ within the set $M_k(R^m)$ of relevant observations. The statistical distribution of the separate estimations for a given link could indicate the robustness of the results.

The relative standard deviation (RSD, as the ratio of the standard deviation to the average) for all links over different time periods is calculated, and the results are plotted as a function of the size of the relevant samples for each link $||M_k(R^m)||$. Here we assume that the significance of the RSD for link R^m is independent from the spatial location of R^m, or at least any spatial variation does not introduce systematic biases. However, we do expect systematic RSD variations across link types (e.g. expressways versus urban streets), because the traffic profiles are different by link type.

Figure 4.46(a) illustrates road-link RSD as a function of size of the sample. As expected, as the sample size increases, the variation of the relative deviation of different links decreases, tending towards the average. **Figure 4.46(b)** shows the cumulative distribution of sample sizes of the links. As seen, at least half of the links base their estimated speed $speed_k(R^m)$ on 16 relevant samples or more, and around 80% of the links are based on four or more data samples. The two plots at the bottom of **Figure 4.46** show the respective RSD distributions for two half-hour time slots (7:30-8:00AM and 9:30-10:00AM respectively).

This confirms our expectation that temporally concentrated samples should result in lower RSD values towards the average RSDs (average RSD is 0.39 for all links between 6:00-11:00AM; 0.32 for 7.30-8.00AM; and 0.33 for 9:30-10:00AM). Moreover, it is also confirmed that different types of links should have different levels of RSDs. The average RSDs of urban streets and low-class road links are 0.40 and 0.39 respectively. On the other hand, the average RSDs of road links (i.e. with speed limits from 90kmh and 120kmh) are much lower, at 0.29 and 0.22 respectively.

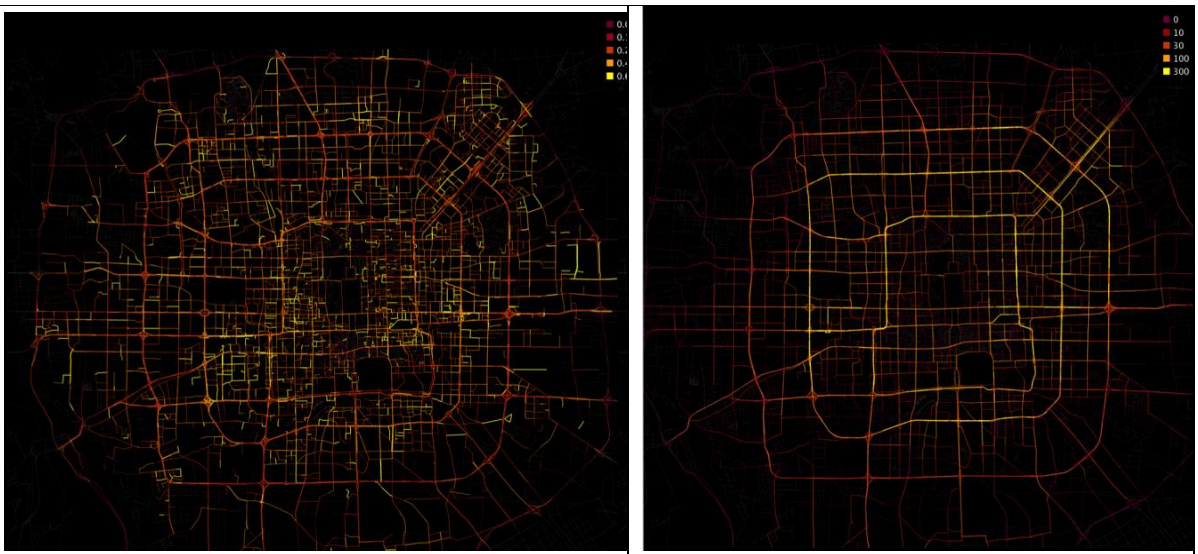
There are higher RSD variations on the lower tier road links. This indicates that there are greater randomness of traffic conditions, higher probabilities to encounter unforeseen congestion and possibly more frequent activities of picking up or setting down of passengers (although we have excluded zero speed links, the traces of taxis slowing down prior to stopping, and taxis accelerating after stopping are still retained in the data). Similarly, the lower RSD values of the high-speed links reflect the natural speed variations (e.g. the speed differences between ordinary and overtaking lanes), indicating better managed and more uniform arterial road speeds.



(a) Relative standard deviation (RSD)
(b) Cumulative distribution of links
(c) RSD 7:30-8:00AM
(d) RSD 9:30-10:00AM

Figure 4.46. Relative Standard Deviation of Sample Size
Source: <Deng et al, 2015>
*Note: <**(a)** Relative standard deviation (RSD) as a function of sample size for the entire morning traffic period (6-11AM); **(b)** Cumulative distribution of links with sample size less than x; **(c)** RSD as a function of sample size for the 7:30-8:00am; **(d)** RSD as a function of sample size for the 9.30-10.00am.>*

Figure 4.47 illustrates the spatial distribution of the RSD values and the respective sample sizes over the full morning period (6-11AM). Apparently, the lack of discernible geographical pattern in the RSD distribution indicates that there is no systematic bias in the estimation of speeds. Furthermore, as we can see, the variance of sample sizes reflects the hierarchical structure of the network, i.e. the higher the road grade, the more road capacity to bear heavier traffic.



(a) Relative Standard Deviation of speed estimations | (b) Number of speed estimations (sample size)

Figure 4.47. Relative Standard Deviation and number of speed estimations
Source: <Deng et al, 2015>
*Note: <**(a)** Relative Standard Deviation of speed estimations; **(b)** Number of speed estimations (sample size) for each link (number of taxi GPS trace links used).*

To further verify the speed patterns across the road network, we calculate a standard road congestion indicator that is independent from the lengths of the road links (**Equation 4.01**). It represents the extra time spent in congestion over free flow conditions required to traverse a metre of the link (measured in seconds per traversed metre of the road):

$$T_{lost}(R^m) = \frac{1}{l_{R^m}} \cdot \left(\frac{l_{R^m}}{speed_k(R^m)} - \frac{l_{R^m}}{speed_{f.f.}(R^m)} \right) = \frac{1}{speed_k(R^m)} - \frac{1}{speed_{f.f.}(R^m)} \qquad \textbf{Equation 4.01}$$

where,
l_{R^m} is the length of link R^m;
$speed_k(R^m)$ is the estimated speed in congested traffic condition of the link;
$speed_{f.f.}(R^m)$ is the corresponding free-flow speed.

This measure reflects the level of congestion in the network; i.e. how much more time is needed per metre under the congested traffic conditions than a vehicle would need if there were no traffic.

Figure 4.48 shows the resulting time lost in traffic $T_{lost}(R^m)$ based on the taxi-GPS speed estimations for the full morning-peak period (6-11AM). The patterns of this indicator are in line with our expectations: the central Beijing area inside the second ring road tends to be the most congested, and the peripheries beyond the fourth ring road are the least congested. The most congested areas are around the Financial Street along west second ring road, the Guo Mao CBD area along the east third ring road and the Zhong Guan Cun area in the science and higher education cluster in northwest Beijing. The urban streets and hutongs with smaller capacities suffer a higher per-metre time loss, because a small increase of traffic tends to cause a sharper rise in congestion level. By contrast, the higher-capacity links, such as the ring and radial high grade roads tend to suffer a more modest per-metre time loss, as the increase in traffic causes a less sharper rise in congestion level till the roads are saturated with traffic (in early 2008 this was rarely the case for the higher grade roads).

Figure 4.48. Time lost (seconds per metre) in traffic based on the taxi-GPS speed estimations
Source: <Deng et al, 2015>

4.6.2. Validation of Congested Speed

We further test the validity of the estimated congested link speed through three different methods, including a minimum-path test for three typical routines, a comparative analysis of 624 origin-destination routes against Google Maps API data, and last a sample-based validation approach.

4.6.2.1. Minimum path test

The first validation is to testify the minimum paths generated by the estimated congested link speeds in comparison of Google Maps recommended routes.

Three pairs of origins and destinations are chosen for this test, including:

(1) A 'shopping in town trip' from Wu Dao Kou (northwest Beijing) to Xi Dan (one of the major shopping centres);
(2) A popular 'tourist trip' from the Beijing South Rail Station (or more precisely, from Ma Jia Pu) to the Olympic Forest Park;
(3) A typical 'commuting trip' from a suburban residential area Wang Jing to the Guo Mao Central Business District (in the middle stretch of the east third ring road).

As these places are surrounded by complex road network and clagged traffic condition, this test is expected to be challenging.

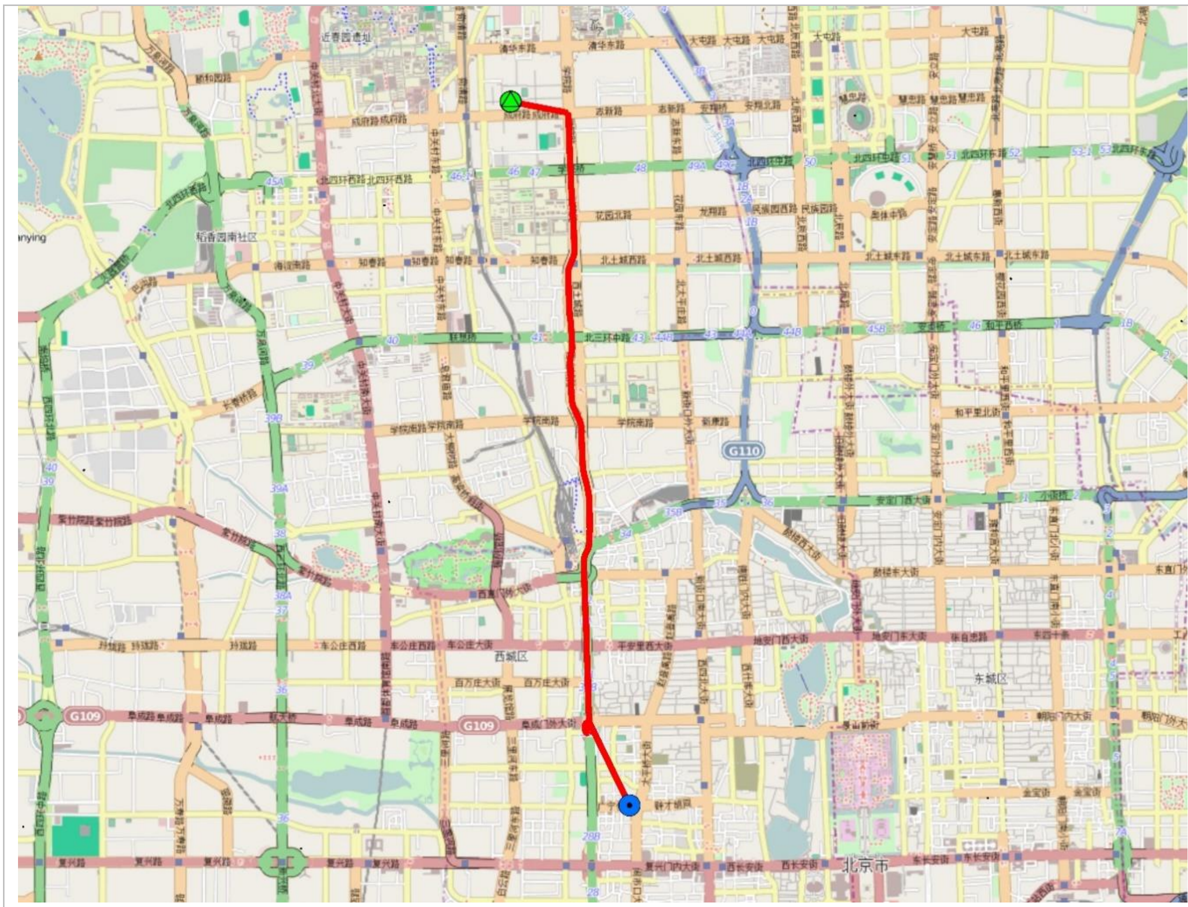
Table 4.21. Minimum-path journey time: modelled vs. Google Maps

No.	Origin	Destination	Test	Estimation (minute)	Google Maps (minute)	Difference	Relative Difference
1	Wu Dao Kou	Xi Dan	1st	28.10	25.00	3.10	12.40%
			2nd	25.50	25.00	0.50	2.00%
			3rd	22.60	25.00	-2.40	-9.60%
			Average	25.40	25.00	0.40	1.60%
2	Ma Jia Pu	Olympic Forrest Park	1st	52.40	47.00	5.40	11.49%
			2nd	50.30	48.00	2.30	4.79%
			3rd	44.90	48.00	-3.10	-6.46%
			Average	49.20	47.70	1.50	3.14%
3	Wang Jing	Guo Mao CBD	1st	24.40	24.00	0.40	1.67%
			2nd	22.40	24.00	-1.60	-6.67%
			3rd	21.40	24.00	-2.60	-10.83%
			Average	22.70	24.00	-1.30	-5.42%

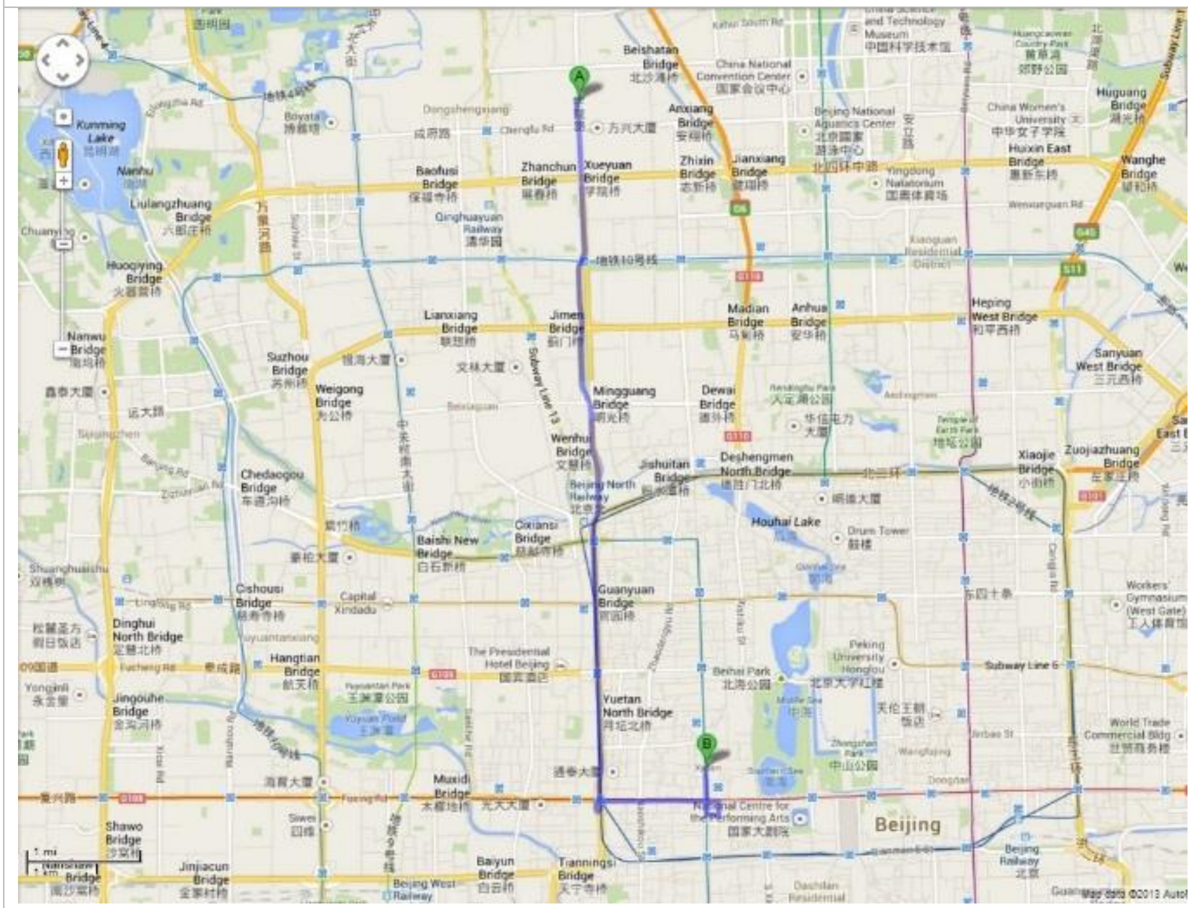
Table 4.22. Minimum-path distance: modelled vs. Google Maps

No.	Origin	Destination	Estimation (km)	Google Maps (km)	Difference	Relative Difference
1	Wu Dao Kou	Xi Dan	13.2	10.2	3.00	29.41%
2	Ma Jia Pu	Olympic Forrest Park	27.8	22.7	5.10	22.47%
3	Wang Jing	Guo Mao CBD	16.1	14.3	1.80	12.59%

The recommended routes from Google Maps were collected over the morning peak on 21 Oct 2013. **Table 4.21** and **Table 4.22** summarises the comparisons of journey time and distance respectively, between modelled routes (minimum paths generated by the estimated speeds) and Google Maps routes. As seen, distances of the modelled minimum paths are 12% - 30% longer than the recommended routes by Google Maps. This is because of the virtual connector links between model zone (origin/destination) centroids and the modelled road network, which are included in the modelled journeys but not existed in reality. The results of journey-time comparisons are more satisfactory with a minor relative difference between approximately -5% - 3% on average.

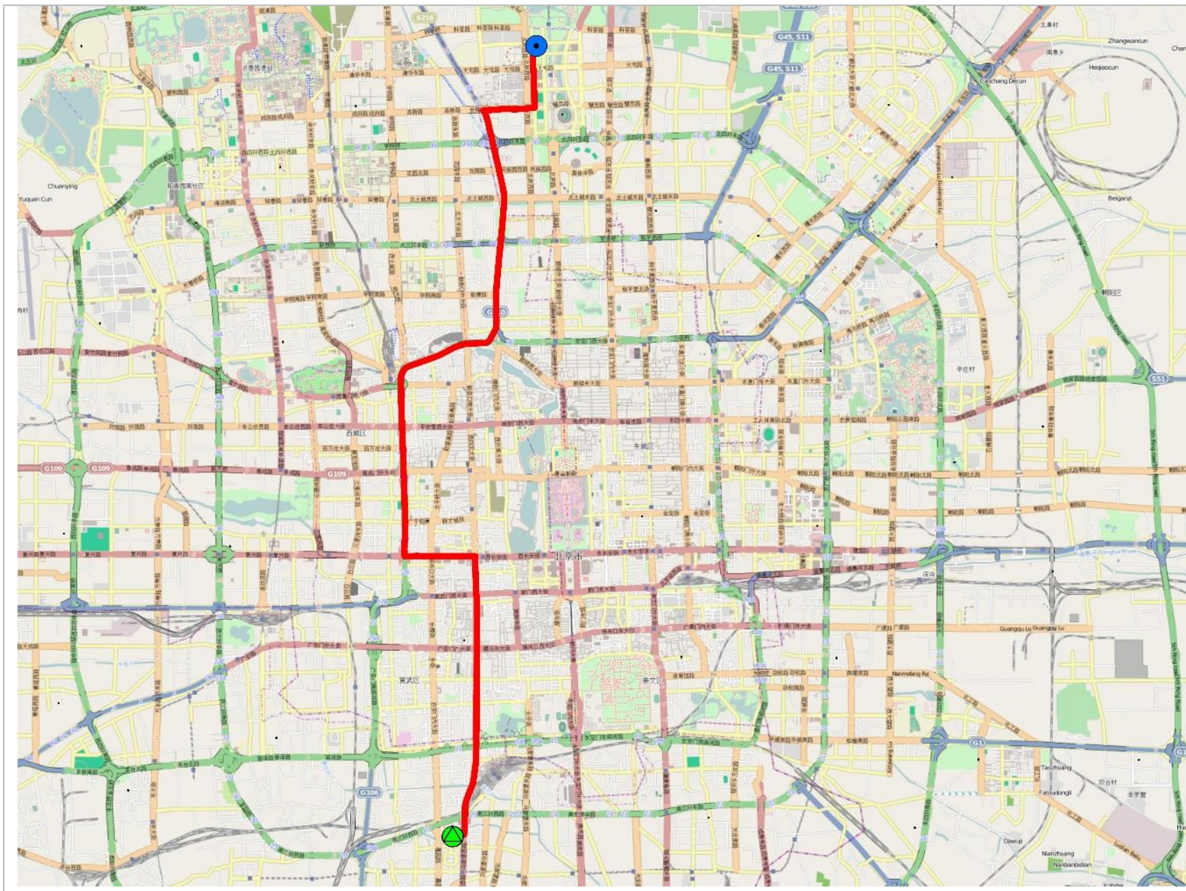


(a) Modelled minimum path

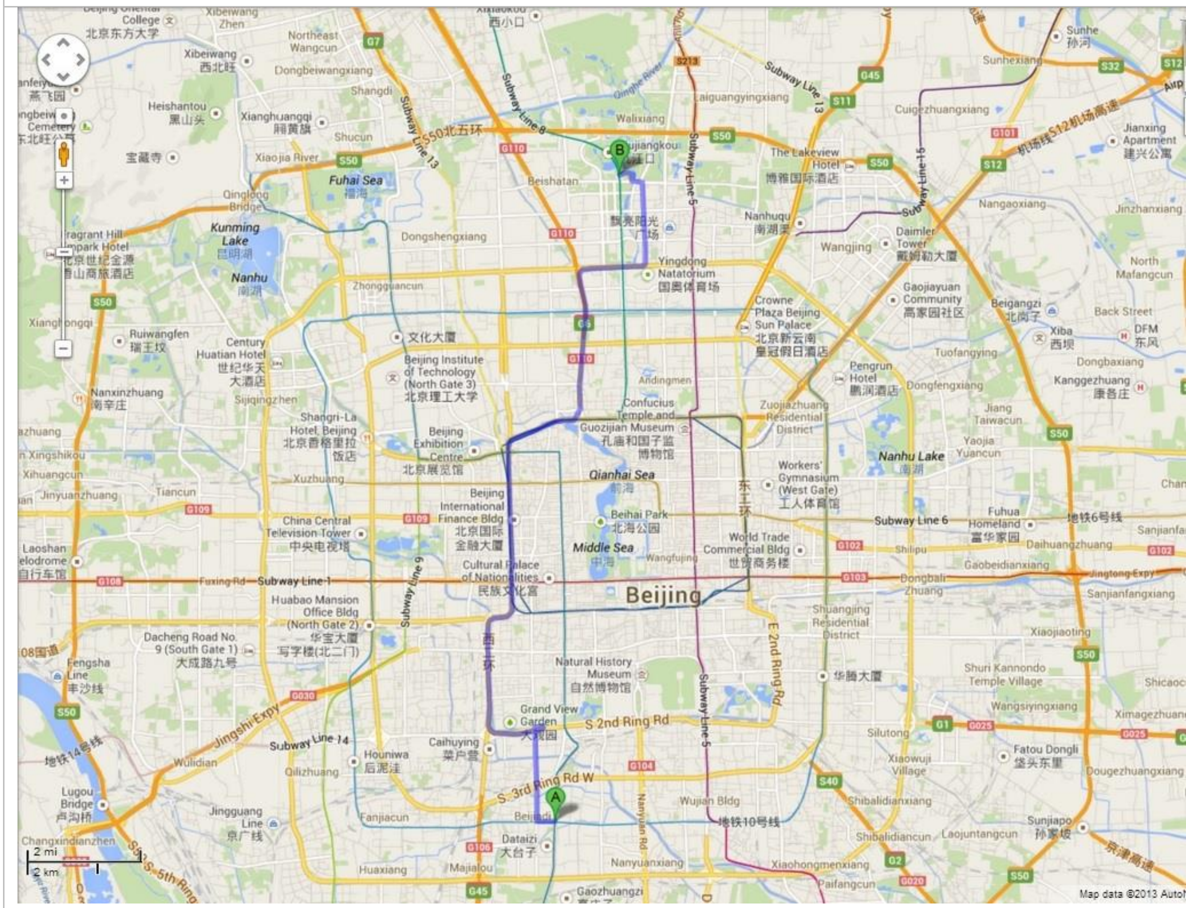


(b) Google Maps route

Figure 4.49. Minimum path: modelled vs. Google Maps: Wu Dao Kou to Xi Dan

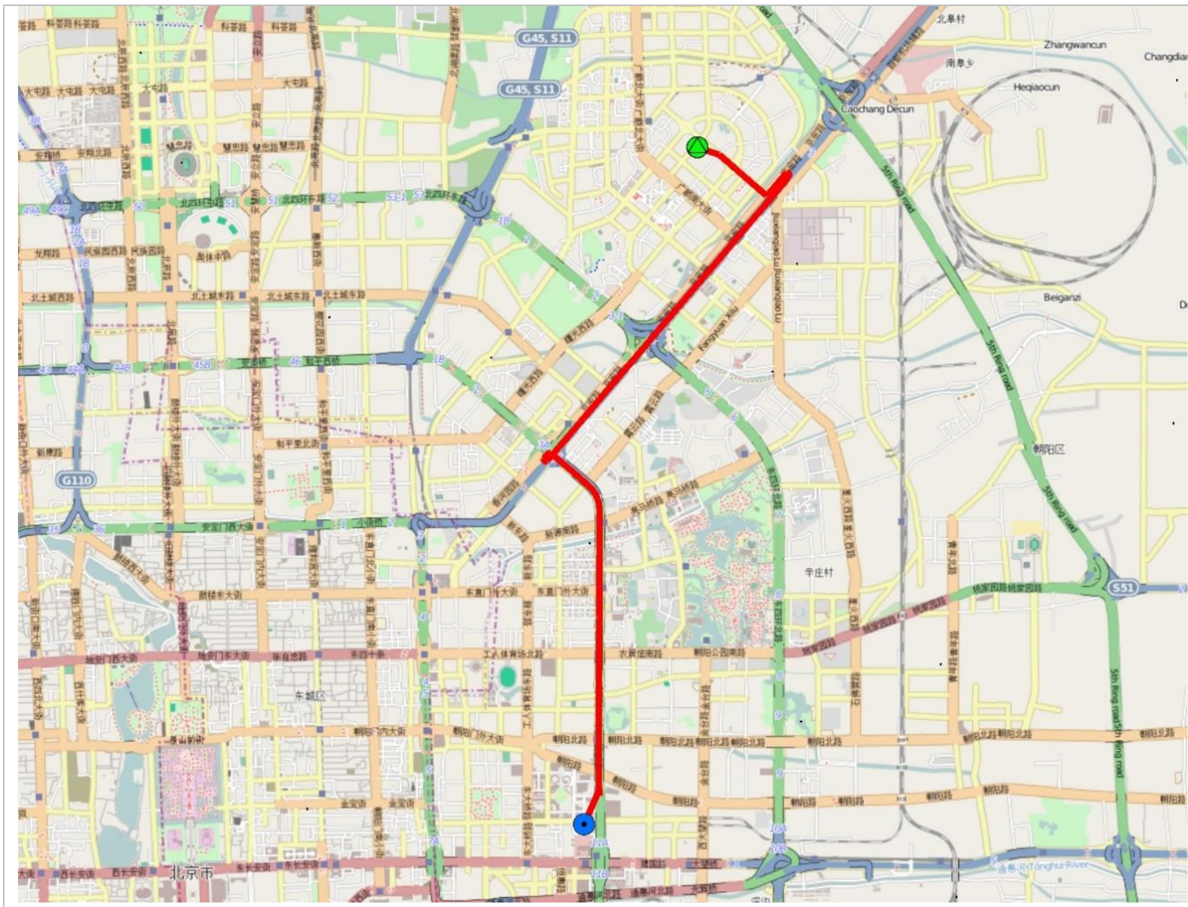


(a) Modelled minimum path

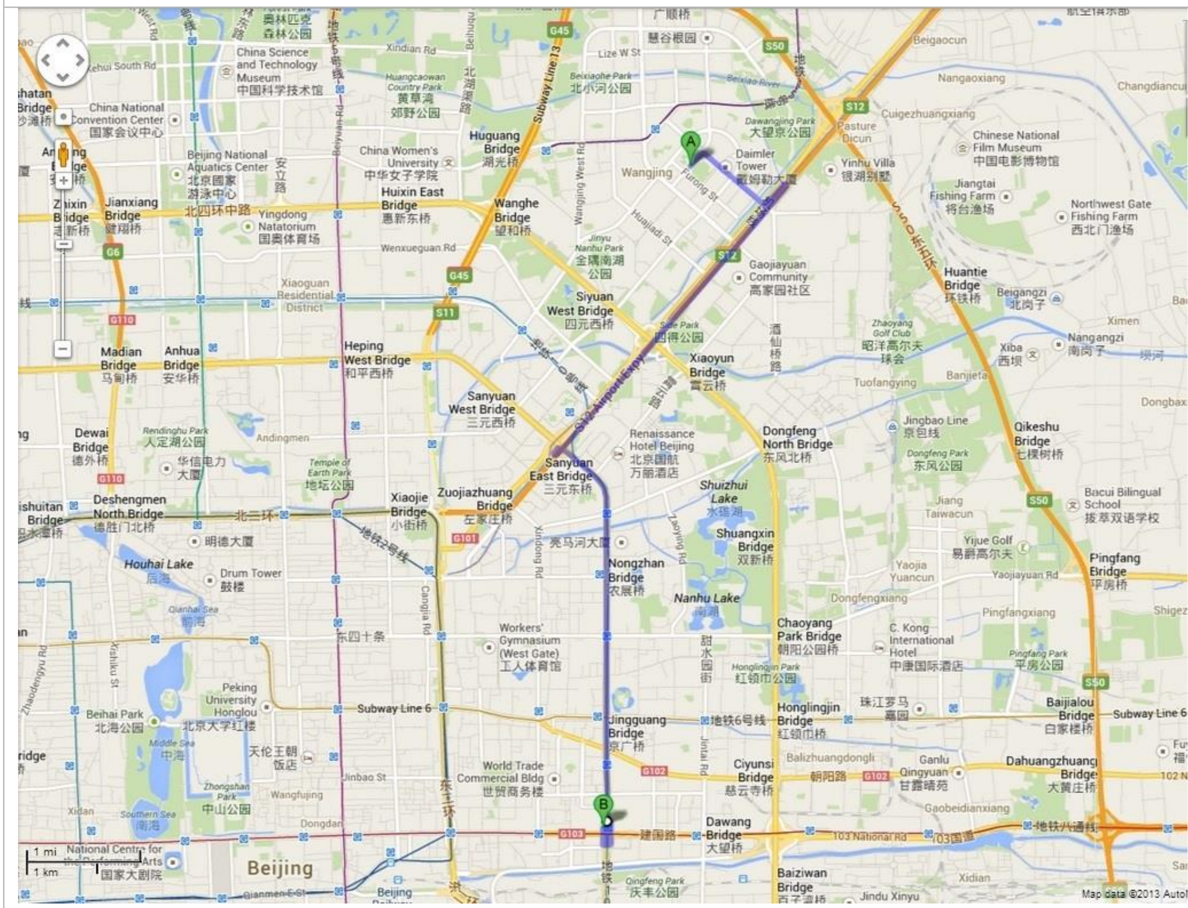


(b) Google Maps route

Figure 4.50. Minimum path: modelled vs. Google Maps: Beijing South Rail Station to Olympic Forest Park



(a) Modelled minimum path



(b) Google Maps route

Figure 4.51. Minimum path: modelled vs. Google Maps: Wang Jing to Guo Mao CBD

Maps in **Figure 4.49**, **Figure 4.50** and **Figure 4.51** illustrate the physical routes of the modelled minimum paths in comparison with the Google Maps journeys, between each of the three origin/destination pairs. As seen, modelled minimum paths are identical to Google Maps, except the minor difference occurred on the southern part of the journey from the Beijing South Rail Station (Ma Jia Pu) to the Olympic Forest Park.

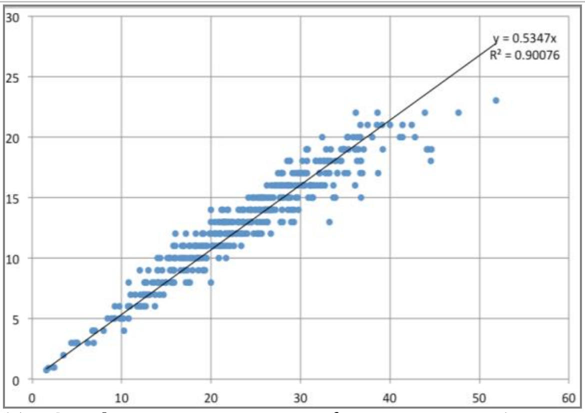
4.6.2.2. Comparative analysis of 624 routes inside the 3rd Ring Road

In addition to checking individual paths through the network, we investigate opportunities for verifying the patterns of estimated travel speeds more comprehensively. For this purpose, we design an approach where OD paths can be generated by the model through the road network with estimated congested speeds, in a form that can be compared with any OD travel time data from other sources. Since there is no available observed travel time data specifically for the data collection days of February 2008, such comparisons are imperfect: the comparison data is only available as estimates, and will not be for the dates of the taxi traces data we use.

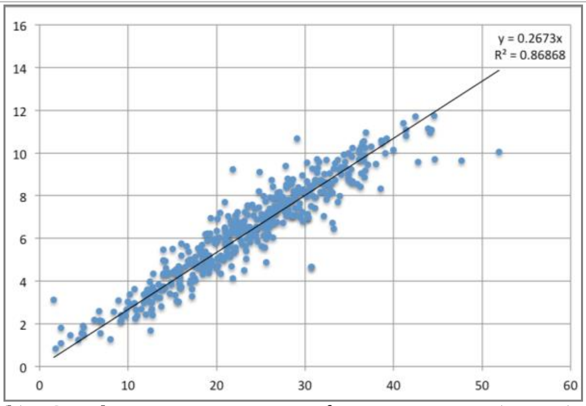
In order to target the most congested area, we have selected six main destinations which are the within the third ring road and generate 624 OD pairs from all possible combinations between 104 origins within the third ring road to the six destinations. For each OD pair, we use the strategic transport model to generate minimum paths by car travel time for the following conditions: **(1)** free-flow network speeds; **(2)** estimated average morning traffic period (6-10AM) speeds; **(3)** the estimated link speeds of each of the 30-minute time-slots within the morning peak period. Our search for the comparison data discovers two sources, both from Google Maps which allows direction search data to be collected: the first is the static non-time-dependent travel times from Google Maps Direction service, and the second is an experimental Google Maps data source that provides 'current' travel times between map locations.

Google Maps Direction traditionally outputs static travel time estimation for a user-defined OD pair. This reflects delays incurred by a traveller on a given transport mode taking account of the circulation characteristics of the network (such as time spent in traffic lights, crossings, left turns etc.) but will not generally account for delays related to traffic. Therefore, putting aside time-dependent road link availability (such as defined by traffic management regulations), the static, non-time-dependent travel times output by the traditional Google Maps Directions service are constant regardless of when the Google Directions service is accessed. However, recently Google Maps started offering time-dependent route duration estimates. These dynamic travel time estimations are labelled “time in current traffic” and are currently freely available only through the Google Maps website; i.e. they are not available through the Google Directions API. These dynamic travel time estimates are based on Google’s estimation of the ‘present’ traffic conditions (i.e. at the time of the directions query) for a subset of the road network. The extent of network coverage varies from extensive to sparse based on data availability, available collaboration with other firms with access to real-time positioning data, traffic feedbacks from public APIs etc. The company has not published detailed documentation on the exact methodology the service uses to estimate “time in current traffic”. Some of the parameters that such a service would have certainly considered include assumptions about the traffic conditions in the part of the road network that is not covered and the prioritisation process; i.e. the method used to evaluate competing routes, some fully within the covered subset, some partially covered and some fully outside it. The latter is bound to be related to risk evaluation and management of uncertainly.

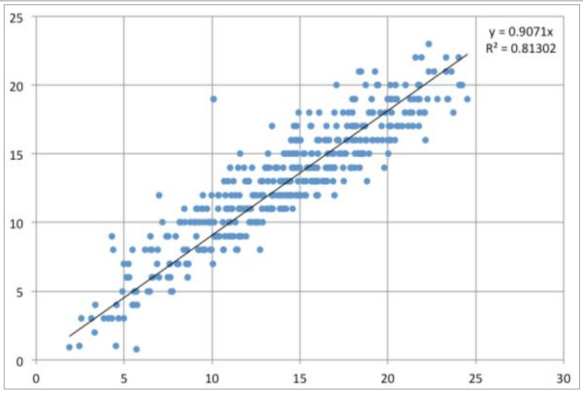
Keeping these limitations in mind and having to deal with incomplete knowledge of how the dynamic routes are generated, such estimations are then compared with the outputs of the route choice modelling process. Factors should be noted include: **(1)** the compared processes run over different modelled networks (Google Maps Direction uses the Google Maps network, and the proposed method uses the modelled network); **(2)** The results from Google Maps were collected in March 2014 (more than 6 years after the Beijing GPS dataset was compiled); the levels of traffic and congestion in Beijing have increased significantly since then; **(3)** The Beijing GPS traces were collected just before the Chinese New Year when the lead up to the festival may contain busier-than-usual traffic during the first two sample days and quieter-than-usual conditions on the Chinese New Year eve. In any case, although the sample volume is still substantial, the data comes from only three working days which is expected to contain a great deal of variability.



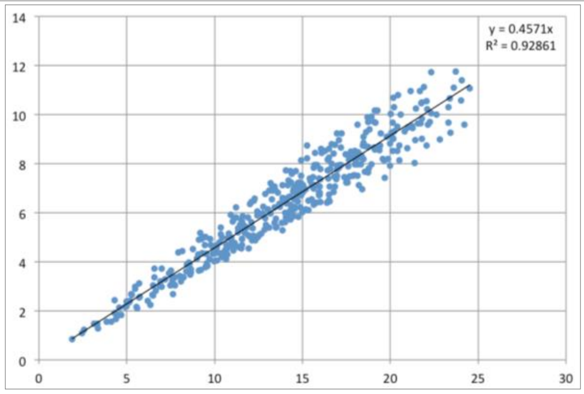
(a) Google Maps: morning-specific journey times (X-axis) vs. non-time dependent journey times (Y-axis)



(b) Google Maps morning-specific journey times (X-axis) vs. modelled free-flow times (Y-axis)



(c) Modelled congested morning journey times (X-axis) vs Google Maps non-time dependent journey times (Y-axis)



(d) Modelled: congested journey times (X-axis) vs. free-flow times (Y-axis).

Figure 4.52. Journey time: Modelled vs. Google Maps

Figure 4.52 demonstrates how the outputs of the two methods compare among **(1)** modelled freeflow travel times for all 624 ODs; **(2)** modelled congested morning travel times for all 624 ODs; **(3)** Google's static non-time dependent travel times for the closest comparable ODs; **(4)** Google's time-dependent 'current' travel times for morning peak travel conditions for the closest comparable ODs.

The comparison shows that:

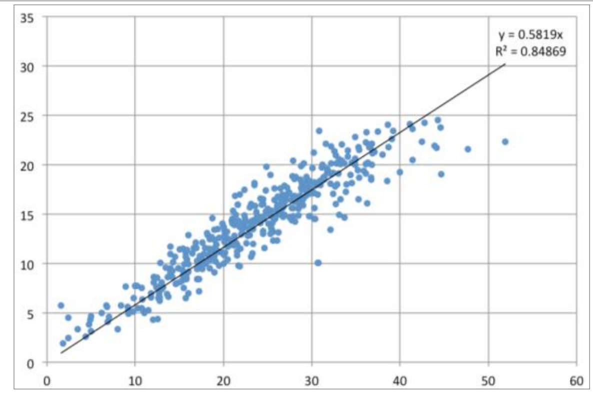
(1) As seen from **Figure 4.52(a)**, there is a significant difference between Google Maps time-dependent and static non-time-dependent travel times; and we understand that the former is representative of the 2014 morning peak conditions, whilst the latter the 2014 average day-time conditions;

(2) As shown in **Figure 4.52(b)**, the modelled free-flow durations are significantly lower than the time-dependent Google Maps time durations; this is to be expected, since the Google Maps travel times reflect the morning peak travel conditions in 2014, whilst the modelled free flow times are for the other extreme, for free flow conditions of the network (e.g. traffic conditions for dawn hours when there are few vehicles on road);

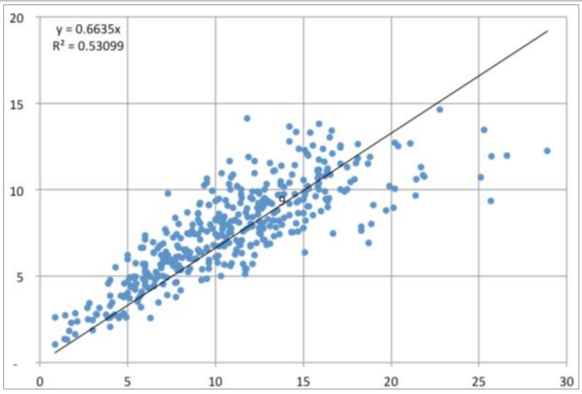
(3) **Figure 4.52(c)** shows that the modelled congested travel times are comparable to, though slightly longer, than the Google non-time-dependent travel times; given that the travel times within the third ring road has increased significantly, particularly since 2010 (as shown by the adoption of the 2012 car purchase lottery measure), it would seem reasonable for the modelled 2008 congested travel times to be comparable to the Google non-time-dependent travel times, rather than their time-dependent morning peak travel times;

(4) **Figure 4.52(d)** shows a comparison of the modelled congested with the modelled free flow travel times – we expect the two to differ significantly, and the comparison is mainly to understand how the travel times correlate.

In fact, all four graphs in **Figure 4.52** display a high degree of correlation (with R^2 being in the range of 0.81-0.93), with little or only minor signs of heteroscedasticity (e.g. for the top-left and bottom-right graphs). This suggests that the estimated congested times are likely to be in a reasonable range, although with the comparisons in this subsection alone it is not possible to provide precise measurements of the error margins.



(a) Modelled (X-axis) vs. Google Maps (Y-axis)



(b) Time lost in traffic: Modelled (X-axis) vs. Google Maps (Y-axis)

Figure 4.53. Journey time and time lost in traffic (morning peak): modelled vs. Google Maps

As shown in **Figure 4.53(a)**, We further compare the time-dependent Google Maps journey durations against our modelled travel times (estimated with the congested speeds) for the morning peak (6-10AM). For reasons stated above, the Google Maps times are longer than the modelled, as expected. It seems to be a good sign that the two data sets correlate well, in fact with a slightly higher R^2 (0.85) than that for modelled times versus Google Maps non-time-dependent (0.81). In the **Figure 4.53(b)**, we compare the time lost in traffic by computing them respectively using the modelled free flow and congested travel times on the one hand, and the Google Maps non-time-dependent and time-dependent morning peak travel times on the other. The comparison results in a relatively high degree of correlation with R^2=0.53. Given the significant variability in the data, this level of correlation would seem encouraging.

4.6.2.3. Sample-based validation

The verification exercises in the above sub sections affirm the quality of the estimated congested speeds in comparison with the journey time information from Google Maps (which is relied by most of us for everyday navigation). In this sub section, we introduce a sample-based validation to scrutinise the level of accuracy and effectiveness of this speed-estimating method itself.

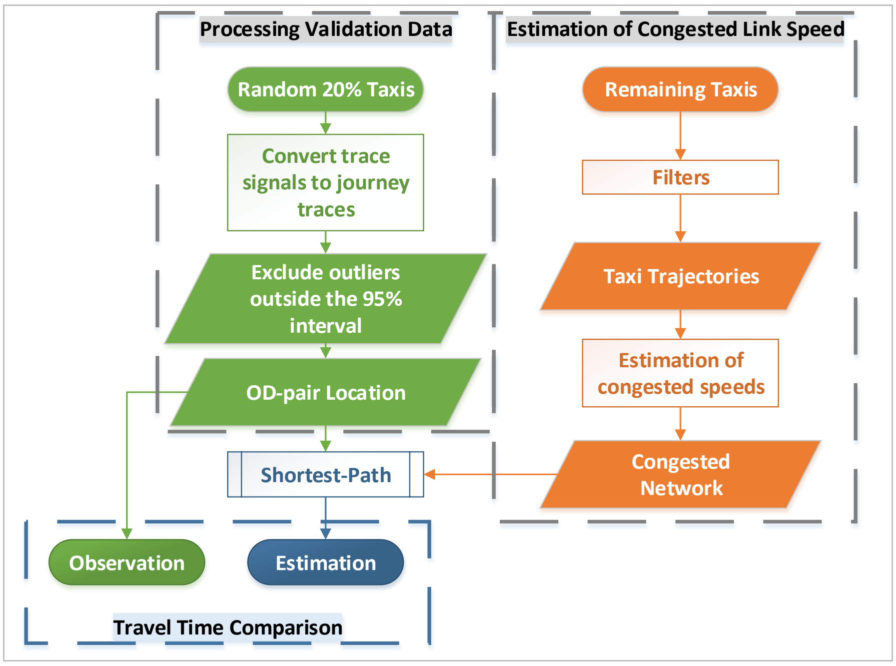


Figure 4.54. Flowchart of the sample-based validation progress

Figure 4.54 demonstrates the detailed flowchart of this sample-based validation progress. As shown, the progress first divides the taxi GPS samples into two separate data sets: a 'Validation Data' set which contains randomly selected 20% (2,071) of the 10,357 taxi data sets, and another 'Estimation Data' set keeps the remaining 80% data samples. Furthermore, the 'Validation Data' set will be used to form observed information (i.e. OD locations and journey times), and the 'Estimation Data' set will run through the congested-speed estimation process. Last, for each observed OD pair from the 'Validation Data', the journey times estimated based on the resulting congested link speed will be compared with the observed times.

- ***Definition of taxi runs in the validation dataset***

As discussed previously, our taxi data does not provide with information about passenger occupancy status or trip origin/destination, but only a series of locations and timestamps. In addition, as the sampling interval is not on a regular basis, there are often long delays between two consequential timestamps. This means that the taxi journey times cannot be derived directly from the timestamps.

In order to create a meaningful comparison, trajectories of 'Observed Data' are simulated through a series of selection criteria to form observed taxi trips. The criteria are as follows:

a) All consequential trajectories belong to one same taxi;
b) The time interval between any two consecutive trajectories is shorter than a pre-defined threshold (two different tests with 60-second and 90-second intervals respectively) of the maximum time interval allowed;
c) There needs to be at least three consecutive timestamps in each run;
d) The start and end locations of each run are different, i.e. only moving taxis are included in the datasets used for comparison;
e) The running distance is no longer than 2.35 times (for sixty-second-interval trips) or 1.91 times (for ninety-second-interval trips) of the crow-fly distances between start and end locations. The ratios of 2.35 and 1.91 are derived from the 90% (by trial and error) of the average ratios among all filtered trips. This rule aims to the remove the noise arising from unrealistically long distances or fast speeds.

A taxi run would be defined when all the above criteria are met. **Figure 4.55** illustrates an example of how the observed trips are initially identified. Points ***p0*** – ***p8*** represent nine consecutive footprints from the GPS traces of one same taxi. The trip identification progress begins with the data point with the earliest timestamp ***p0***, calculating the time different between this point and its following point ***p1***. If the time interval between ***p1*** and ***p0*** is smaller than a pre-defined threshold ***r***, then it will repeat the process to the next following point; otherwise ***p0*** will be considered as a noise and the search will start from its next following point. This process will not stop until the time difference between $\boldsymbol{p^{i}}$ and $\boldsymbol{p^{i-1}}$ ($\boldsymbol{i \in 1, 2, \ldots, 8}$) turns out to be greater than ***r*** (e.g. ***p5*** and ***p4***). If there are three or more data points from ***p0*** to $\boldsymbol{p^{i-1}}$, then the trace in between will be defined as an initial taxi run (trip); otherwise these points will be regarded as noises. This process will repeat and traverse all data points to find all the valid initial taxi runs (e.g. ***Run T1*** from ***p0*** to ***p4***, and ***Run T2*** from ***p6*** to ***p8***).

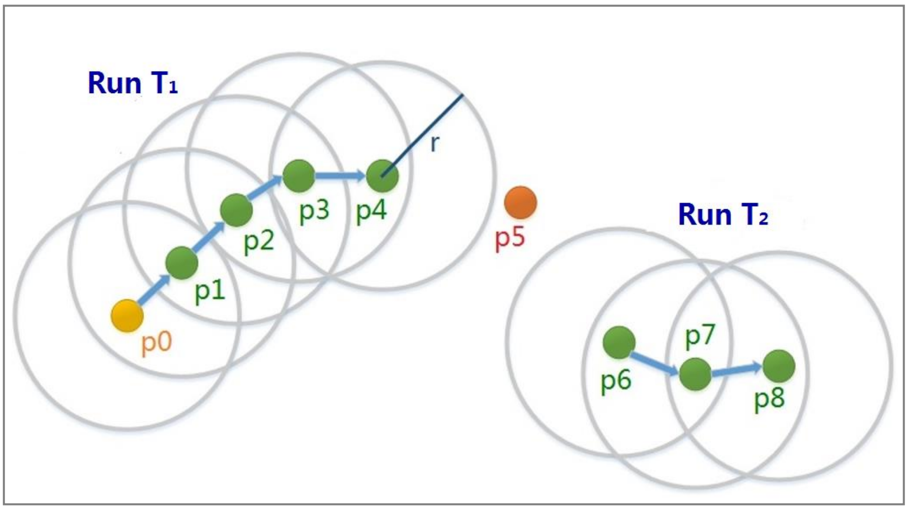


Figure 4.55. Example of observed taxi runs

In this study, we generate two different sets of observed taxi runs, with ***r*** value defined as 60 and 90 seconds respectively, based on the same trajectories from the randomly selected 2,071 taxis on 4th February 2008. As shown in **Table 4.23**, following the taxi-run identification progress described above, there are initially 1,416 and 1,320 taxi runs identified respectively for 60s and 90s time interval thresholds. Sifting through the distance-ratio filter and the 90% confidence interval in journey time, there are 876 and 805 taxi runs remaining respectively, which will be used as observed taxi runs in the validation.

Table 4.23. Number of simulated 'observed' taxi runs

Time-interval Threshold (*r*)	Number of taxi runs		
	Identified	Distance-ratio Filtered	90% Confidence Level
60 seconds	1,416	973	876
90 seconds	1,320	894	805
Total	**2,736**	**1,867**	**1,681**

It is worth noting that this cleaning process is very strict (i.e. between 6:00 – 11:00AM, the GPS data of the randomly selected 2,071 taxis give rise to only 2,737 raw taxi runs prior to the filtering process). This is because that here we aim to simulate reliable 'observed' taxi runs, and to select the runs with the most accurate journey time information.

- ***Generation of the congested link speed from the experimental dataset***

Congested link speeds are estimated by the method presented above for each 30-minute period during the full morning period (6:00 – 11:00AM) using 'Estimation Data' set. It is worth noting that where a link is not covered by taxi traces data (because the data points are fewer for estimation where they are divided into time periods), the estimated average congested link speed for its link type and time period is adopted (as show in **Table 4.24**). This infill by average link type speeds helps to create road networks with congested speeds for each half-hour time period within the fifth ring road of Beijing.

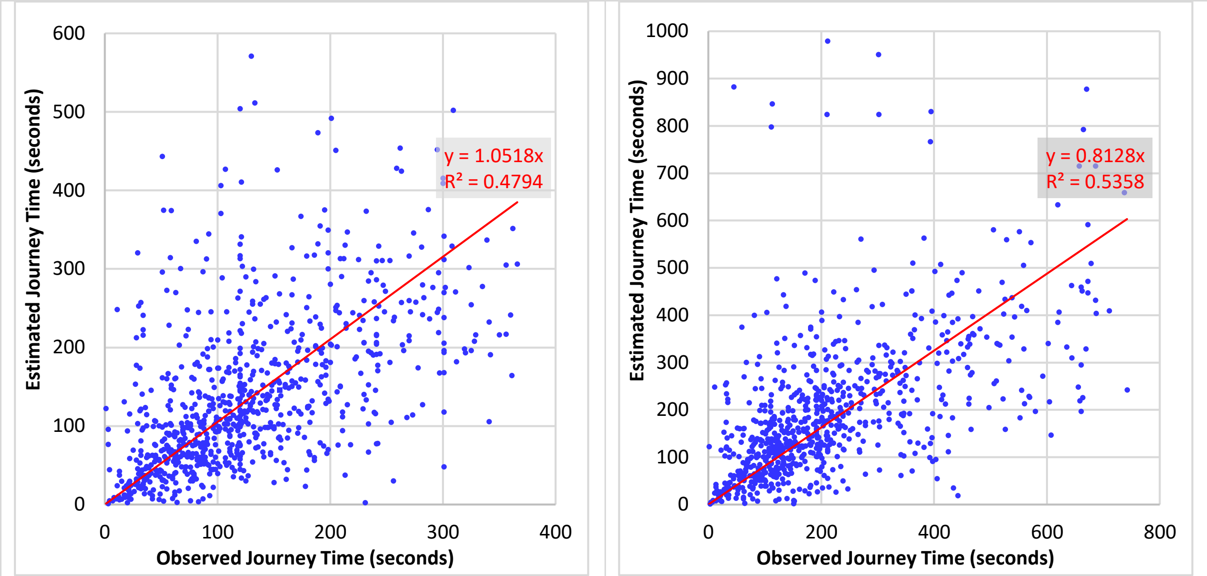
Once the link-level congested travel times are estimated, we run the transport model to obtain an estimated travel time on the modelled road network from the origin to the destination locations of each of the identified observed taxi runs. The networks specifically estimated for each half hour period are used based on the start time of the observed taxi runs. For example, for a run beginning at 10:06am, the modelled travel time is estimated using the 10:00-10.30am congested road network.

Table 4.24. Average congested link speeds (km/h) by broad link type /half-hour time period

Link Type	**Average Congest Link Speed (km/h) – AM Time Period**										
	6:00 – 6:30	6:30 – 7:00	7:00 – 7:30	7:30 – 8:00	8:00 – 8:30	8:30 – 9:00	9:00 – 9:30	9:30 – 10:00	10:00 – 10:3	10:30 – 11:00	**Ave. AM Peak**
4th level/ unclassified	22.2	19.9	22.2	20.6	20.9	19.3	19.2	18.1	18.3	18.1	**18.6**
2nd ring /3rd level road	28.5	29.0	28.0	28.3	27.6	25.9	25.2	23.7	23.4	23.6	**25.1**
3rd ring /2nd level road	33.2	33.2	32.7	32.6	31.2	29.5	28.4	27.0	27.0	26.8	**29.2**
4th ring /1st level road	40.2	39.5	39.1	36.8	37.5	35.6	32.4	30.1	31.2	30.8	**33.6**
5th ring / expressway	55.2	57.0	56.0	54.6	52.7	49.6	47.0	45.1	44.9	45.1	**47.9**
6th ring	74.1	78.8	71.2	75.9	71.8	64.2	71.5	67.8	61.3	66.4	**68.9**
6th ring/ expressway	61.4	69.3	62.7	63.2	63.1	59.9	58.4	53.8	52.1	55.6	**58.1**
expressway	80.2	76.4	76.4	72.4	72.6	67.1	68.2	67.0	66.1	65.4	**69.7**

- ***Analysis of validation results***

Figure 4.56 demonstrates the comparison between modelled and observed journey times for taxi runs that have been identified using time-interval thresholds (***r*** values) respectively of 60 and 90 seconds (**Figure 4.56(a)** and **(b)** respectively**)**. The comparison suggests that when the taxi runs are generated with a 60-second maximum interval (***r***), the method produces modelled-trip travel times that are more satisfactorily comparable with the retained validation data. The heteroskedastic pattern (i.e. the margin of error for the modelled versus observed becoming larger as the durations of the trips are larger) is to be expected, since an average travel time estimated off the model network is compared with individual taxi trajectories. However, the estimated journey times for taxi runs in aggregate are some 5% higher than the observed, as indicated by the linear fitting slope of 1.05. For this 'Validation Data' set, there is no indication that the exclusion of zero speed taxi runs has biased the estimated traffic speeds upwards.



(a) 60s time-interval threshold (b) 90s time-interval threshold

Figure 4.56. Journey time comparison: observed (X-axis) vs. estimated (Y-axis)

It shows a bigger discrepancy in the comparison of journey times between estimations and observed taxi runs with 90-second time-interval threshold: the estimated trip times are some 19% below the observed (i.e. with the slope being 0.81). It is not entirely clear what the reason behind is, but since the traffic signal time intervals are mostly within sixty seconds, this sharp change in the comparison indicates that there may be something special with signals that have a time interval of 60-90 seconds. We could speculate that such delayed intervals might be caused by either the observed times having been prolonged by non-traffic delays (e.g. detours and waiting for customers), or some other operational features/data errors in the dataset. Given that the short taxi pick-up/set-down can take between 60-90 seconds, it would be reasonable to suggest that the data with 60-90 second intervals might contain such non-traffic delays. However, we will have to wait till better quality data becoming available in the future to ascertain such speculations.

There is another issue with the estimation, which is to do with the reduction of the number of observations used to estimate congested link speeds. Although the total number of observations in the original dataset is reasonably large, the road network also contains a large number of links. This means that in some instances there may be relatively few observations in parts of the network for estimation. The use of average speeds by link type to infill the missing data may have also introduced some errors, although it would seem unlikely for that to introduce systematic errors.

Although the linear fitting curves are broadly acceptable, there are errors when comparing individual pairs. More precisely, the median values of proportional absolute error of estimated travel times are 36.8% and 37.4% respectively for sixty-second and ninety-second threshold trips. This means that for all the 1626 observed taxi runs, there are 50% (813) of them, have estimated travel time with error smaller than 37%, when comparing with the observed travel times. Whilst we recognise the potential variability of the observed data when using individual observations for validating estimated averages, this clearly leaves rooms for improvement in the quality and quantity of observed data.

Overall, the validation exercise above suggests that the proposed method can provide satisfactory estimation of congested road link speeds across a network in the size of Beijing. These congested link speeds produce estimated travel times for a randomly generated sample of trips that are within acceptable levels when compared with observed travel times. This is especially true when the trips are generated using time intervals of no longer than 60 seconds. Meanwhile the median values show that there are 50% of the 1626 estimations having errors smaller than 37%. These errors are inherent with such datasets with low or inconsistent precision of individual observations. Better quality data may also in the future provide opportunities to improve the methods applied here.

4.6.3. Congested Link Speed for Outside Beijing's Fifth Ring Road

For links outside Beijing's Fifth Ring Road, where the Taxi GPS trace data is sparse, their link speeds are calculated by link type (instead of individual link) in order to make a sensible use of the sparse data. In some instances, when a link type in external area is not covered by the taxi trace data at all, a ratio of congestion level is assumed in line with the available estimations in this area.

Table 4.25 summarises the key information about the calculation of the congested speeds on the road network outside the Beijing Fifth Ring road, including:

(1) Average free-flow speed assumed for the link type;

(2) Number of links (by a specific link type) which are covered by at least one GPS-generated link speed;

(3) The resulting link-length-weighted average congested link speeds, which will be later applied to those links without any GPS signals;

(4) The congestion ratio, as the average congestion speed divided by average free-flow speed for each link type, which will be used for deriving congested link speeds for external road network.

It is worth noting that metro and railway links do not require congested speeds – there may be overcrowding on trains which can be modelled, but in the Beijing model we don't need to model that, as our aims are to estimate the demand of rail travel, and consider rail and metro investment that can meet this demand.

Table 4.25. Congested link speeds outside Beijing's Fifth Ring Road

Link Type	Free-flow Speed (km/h)	Number of Links in Estimation	Length-weighted Ave. Congested Speeds (km/h)	Congestion Ratio
1001	120	52	79.3	0.661
1002	110	35	60.9	0.553
1004	100	83	54.5	0.545
1006	100	101	55.4	0.554
1012	120	61	70.0	0.583
1030	120	2	76.3	0.636
1051	100	10	69.3	0.693
1102	100	62	54.1	0.541
1106	120	100	52.2	0.435
1111	100	72	62.3	0.623
3200	80	445	42.6	0.533
3201	80	596	29.8	0.372
3203	60	1,036	25.2	0.420
3205	50	2,317	22.1	0.442
3207	40	326	15.0	0.375
3300	80	537	43.8	0.548
3301	80	439	33.5	0.418
3303	60	694	27.0	0.451
3305	50	2,767	23.4	0.468
3307	40	1,174	18.6	0.466
3400	80	541	53.3	0.666
3401	80	294	35.6	0.446
3403	60	981	29.7	0.496
3405	50	2,961	26.0	0.520
3407	40	966	19.5	0.487
3500	90	309	69.5	0.772
3501	80	284	40.2	0.503
3503	60	1,238	33.4	0.557
3505	50	2,471	28.6	0.572
3507	40	1,182	22.6	0.565
3601	80	14	40.9	0.511
3603	60	60	43.5	0.725
3605	50	57	37.7	0.754
3607	40	12	15.5	0.387
All	**-**	**22,279**	**28.7**	**0.538**

4.7. Verification of the Free Flow and Congested Transport Networks

This verification test further examines the appropriateness and reasonableness of the minimum paths for car trips throughout the modelled road network, using the assumed free-flow and the estimated congested link speeds respectively.

Five destinations have been chosen for the test, covering all the central urban and peripheral areas (**Table 4.26**). The five destination zones distribute at the centre and four corners of Beijing respectively, and hence the minimum paths to them would be able to reflect the topology and accessibility of the road network in Beijing. As shown in **Figure 4.57** – **Figure 4.61**, minimum paths with both free-flow and congested speeds are broadly reasonable, affirming an adequate degree of assurance for their use in model applications.

Table 4.26. Destinations for minimum-path test

No.	Destination
1	Xicheng District
2	Fangshan District
3	Majuqiao
4	Capital International Airport
5	Dong Xiao Ying

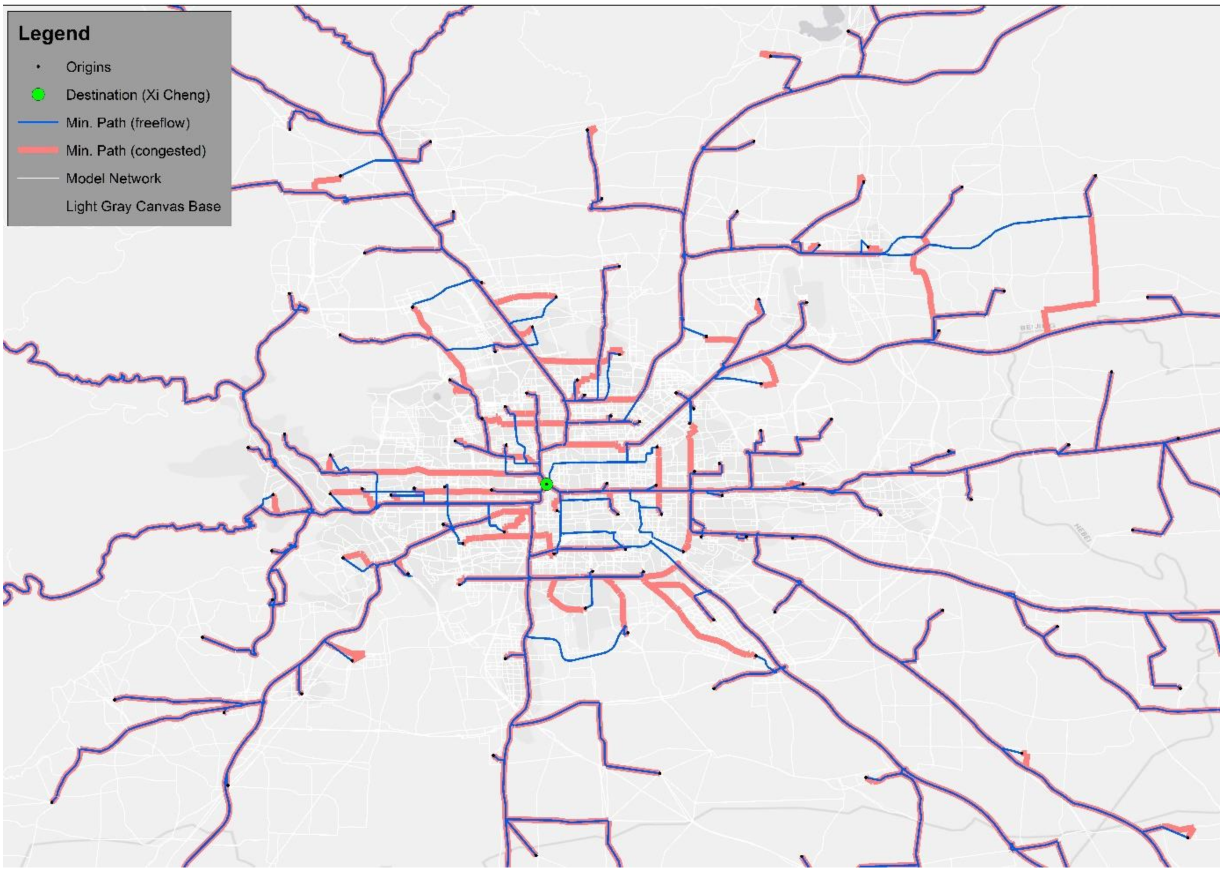


Figure 4.57. Minimum paths from all other model zones to Xicheng District

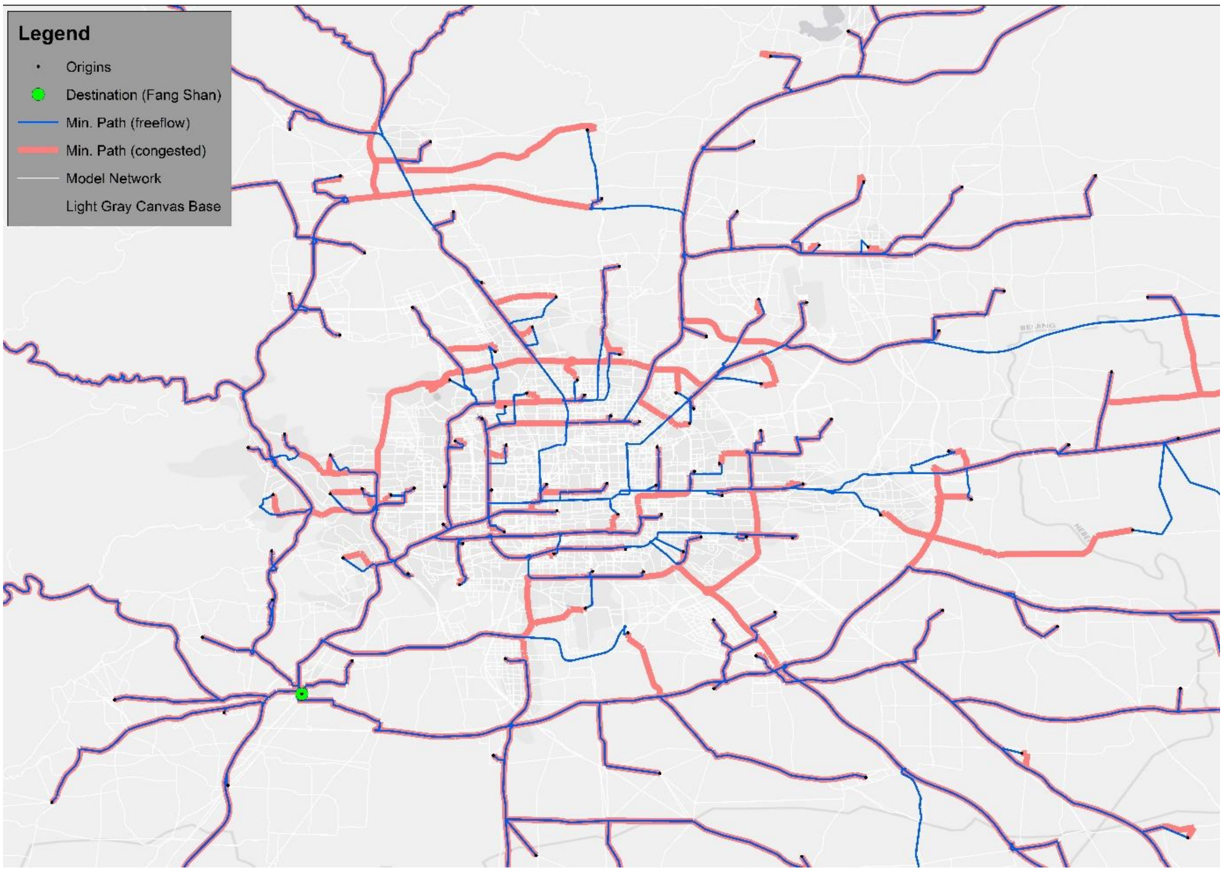


Figure 4.58. Minimum paths from all other model zones to Fangshan District

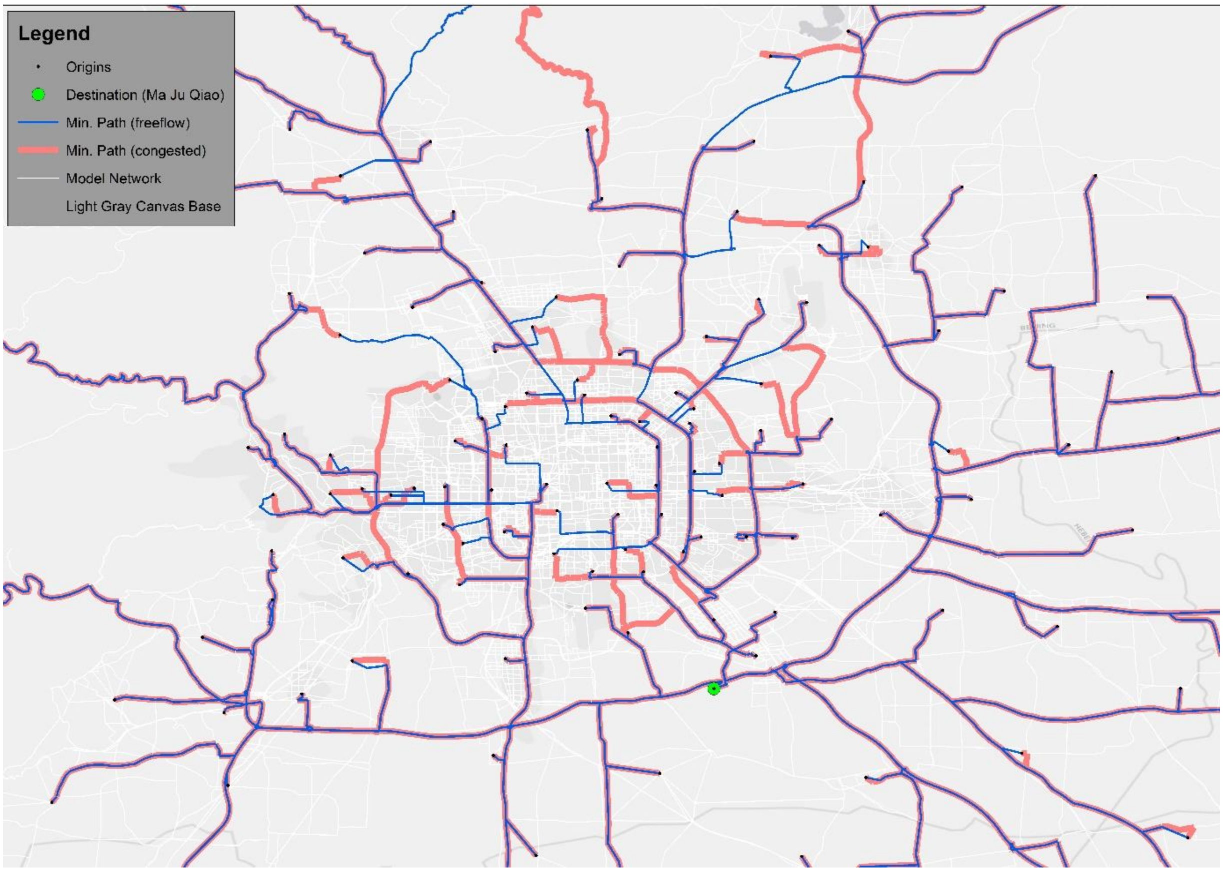


Figure 4.59. Minimum paths from all other model zones to Majuqiao

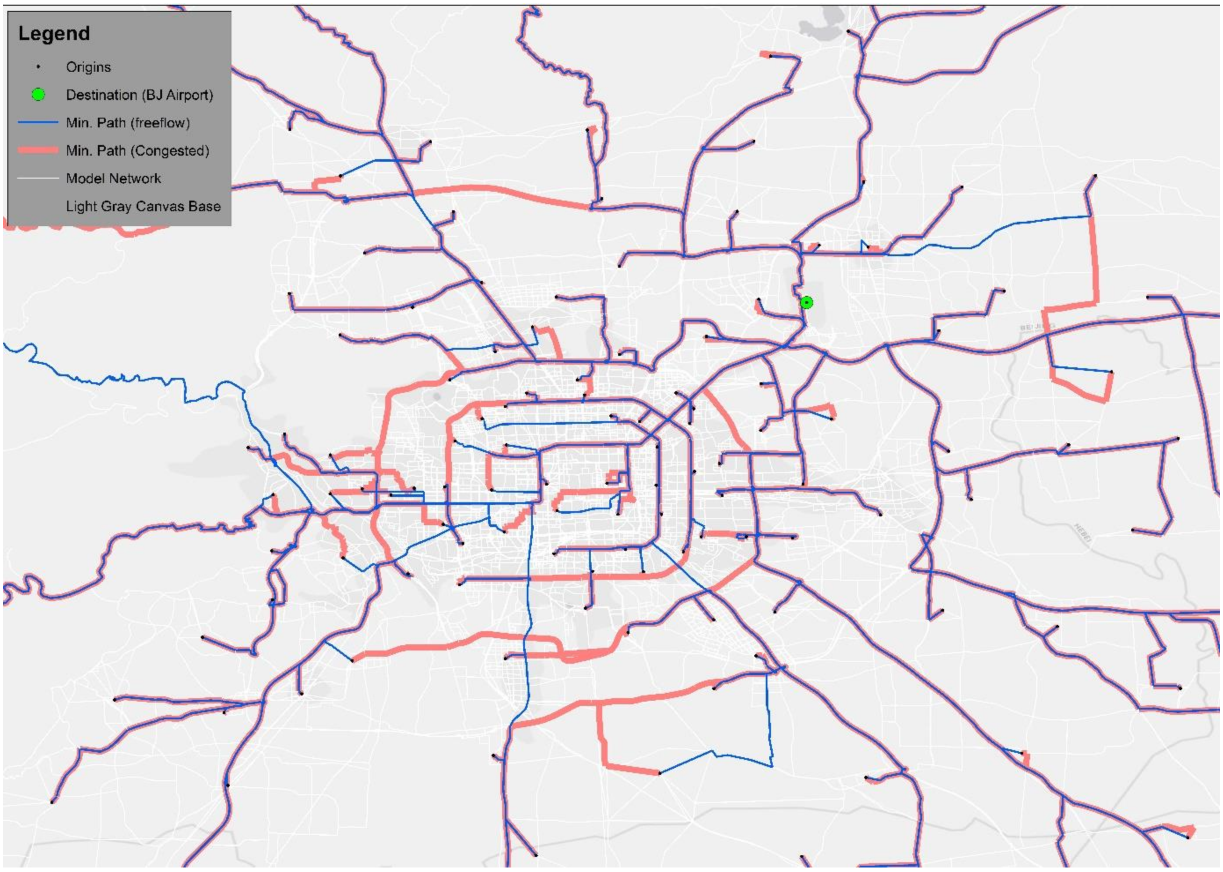


Figure 4.60. Minimum paths from all other model zones to Beijing Capital Airport

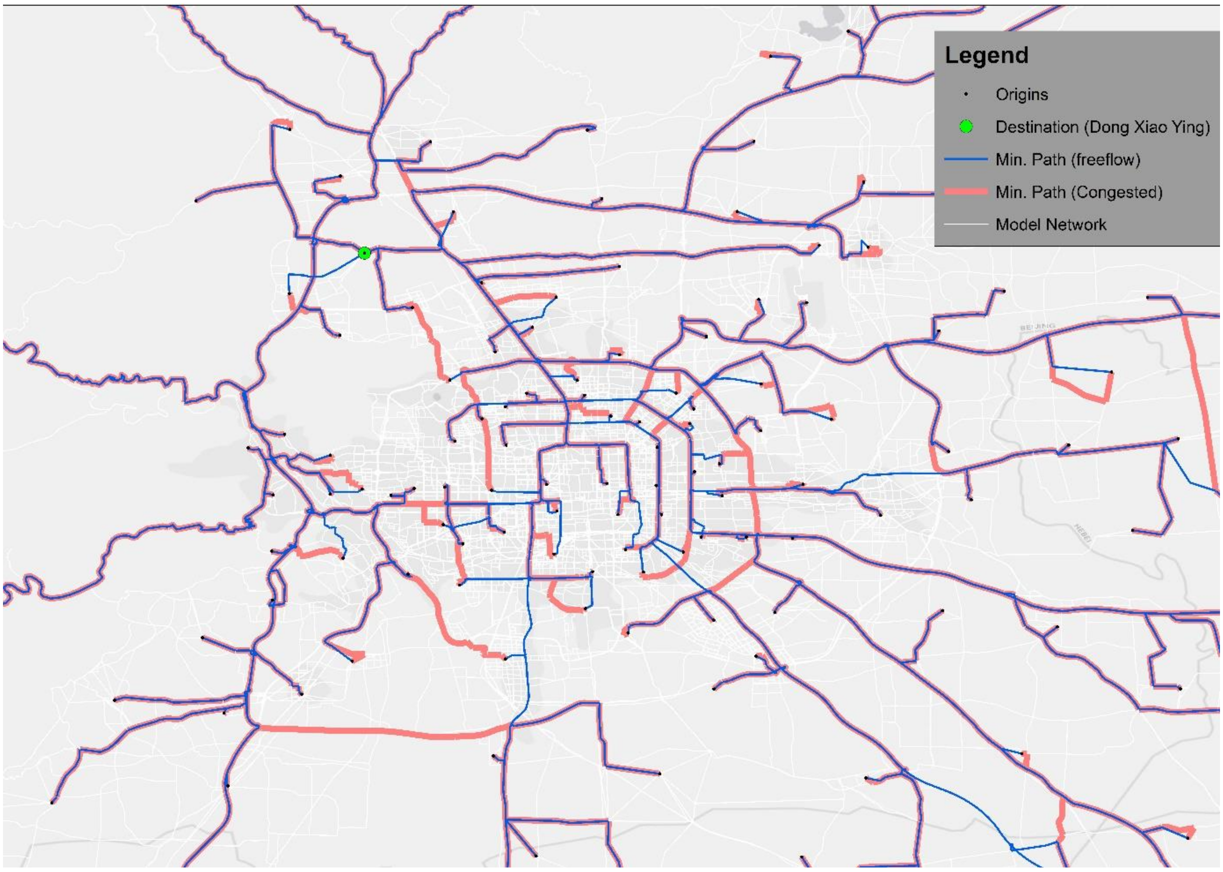


Figure 4.61. Minimum paths from all other model zones to Dong Xiao Ying

4.8. Land Use and Travel Demand Modelling

Having addressed the four bottlenecks we have identified in **Chapter 3** (i.e. interzonal transport networks, intrazonal supplementary networks for strategic models with large zones, understanding of the vehicle GPS traces and estimation of congested road travel times), we turn to the assembly of the strategic transport model. As discussed in **Chapter 3**, in order to fill the most apparent gap in developing the urban transport systems in emerging economy cities, the strategic transport model must involve the prediction of the patterns of jobs and households in the medium to long term (i.e. at least 10-20 years). This is particularly required for addressing the missing link in transport infrastructure planning which is a robust analysis of the the medium to long term scenarios of broad transport demand patterns across the city region, given the continuing surge in the number and proportion of urban population, income levels and consumer demand for goods and services.

In line with the discussions in **Chapter 3**, we focus the articulation of the modelling system based on a broad scenario assumption that the morning peak travel times in the medium to long term will remain at an acceptable level, and we use the model to explore the implications of this type of scenarios for land use planning and infrastructure investment. We choose this focus because currently few studies are carried out this way. Of course the model design should also cover the more conventional applications such as testing incremental land use and transport changes such as arising from government's planning and investment measures – such conventional applications may be required in assessing the marginal impacts of individual projects or regulatory measures in day to day planning and policy work.

In this model, we interface the strategic transport model with RSE-Beijing, which is a spatial economic and land use model that has strong economic and behavioural underpinnings for production, consumption and medium to long term recursive spatial equilbrium process (Jin et al, 2013; 2015). This would enable us to develop the strategic transport model more quickly and transparently, whilst being able to test medium to long term transport scenarios with sensible land use patterns.

This means that the articulation of the modular model structure would consist of the three main components in line with the discussions in **Chapter 3** (**Section 3.2.1**): **(1)** the first component is an external spatial economic and land use module (i.e. RSE-Beijing) which produces the predictions of jobs and household locations (Jin et al, 2013; Jin et al, 2017; Wan, 2016); **(2)** the second component is an internal land use activity and travel demand model (Jin et al, 2013; Jin et al, 2017; Rong, 2016). Its role within the strategic transport model is to generate production-consumption matrices based on the exogenous acitivty location information from the RSE model and retain the capability of testing marginal changes in land use activity and trip distribution patterns without going back to RSE-Beijing. This module also includes the interface that coverts **(a)** production-consumption matrices from the this module to origin-desination (OD) matrices for transport modelling, and **(b)** day/morning peak period transport costs and times from transport modelling to monthly costs and time outlay for this module**. (3)** the third module is the strategic transport model, which is the core of this research. The strategic transport model executes two main task, including: **(a)** modal choice, which splits the OD matrices above to different modes for interzonal travel and in the case of intrazonal travel, both intrazonal distance ranges and travel modes within each distance range; and **(b)** network assignment, which disttributes the modal travel from modal split module and assign the road and rail traffic onto individual paths and network links based on the respective costs and travel times coded for each link.

In addition to these main components, the assessment module that examines the differences between policy scenarios in terms of economic, social and environmental impacts, is readily mature approach to assesse policy scenarios using results from strategic transport models (see e.g. Echenique et al, 2013; Jin et al, 2017). For this reason we do not develop a new assessment model, but instead will focus on providing the inputs to this module, and augment the approach through a new method for assessing medium to long term travel demand given a specific spatial pattern of acceptable travel times in a future year (e.g. Echenique, 2004).

In line with the model design above, the strategic transport will the patterns of travel demand estimated from the land use model, and examine how much different parts of the transport network will be under pressure in different investment, regulation and pricing scenarios. The mode choice module and network assignment module are implemented using MEPLAN software, under a permission from WSP Group for academia use at Martin Centre. While the travel demand and land use modules are part of the RSE model results (Jin et a, 2013; Jin et al, 2017; Wan, 2016; Rong, 2016).

The workings of the strategic transport model can be discussed separately for model calibration for a Base Year and for model predictions in a future year. **Figure 4.62** presents a summary of the workings of the model for model calibration for the Base Year of 2010. Note the labelling of each steps below corresponds to the labels of the model steps (such as ‘(a)’ in **Figure 4.62**):

(a) The 2010 model calibration starts with an input of exogenous land use data from RSE-Beijing. The main reason for inputting the land use data from RSE-Beijing rather than directly from land use statistical data tables (like in the UK) is that the Chinese Population Census, Economic Census and floor space data are less well connected and cover a more limited range of statistics. For instance, the Population Census does not have information on residents' job locations; job locations have to be estimated from an Economic Census (for the majority of non-agricultural jobs) from a different year supplemented by other sources to cover all jobs; in addition to family households, there are 'collective households' who include a variety of different types of permanent residents (such as those recently recruited by Beijing companies and institutions from outside Beijing) and temporary ones (such as university and college students living in dormitories which are concentrated in a number of university and college areas in the cities); the housing statistics are only available at the urban district level which are larger than model zones; the floating population (i.e. short-term visitors staying for less than six months), of which there are 1.8 million in Beijing alone is not included in the population censuses. Furthermore, the population census data does not provide data on socioeconomic or income classifications. The above data has been estimated in the development of RSE-Beijing in an identical zoning system and therefore can be obtained directly. In addition, the input-output coefficients have been estimated in RSE-Beijing alongside the zonal data estimate, which can be adapted for use in the MEPLAN land use and travel demand model.

(b) The zonal data inputs of employed residents, employed workers, non-employed households, university and college students and floating population form the main land use activity inputs. The input-output coefficients in the form of a social accounting matrix (SAM) are also obtained from RSE-Beijing which specifies how jobs demand employed resident labour, the formation of households by employed residents, the composition within employed and non-employed households in terms of persons by age group and employment status, demand for goods and services, different non-commuting trips, etc.

(c) The land use activity and travel demand model is then run for calibration, using information from the Beijing family expenditure survey to check consumption patterns across the urban and rural zones in the Greater Beijing region, and using the trip rates and mode choice data reported in BTRC (2012) to fine tune the concentration parameters such that the average journey lengths by trip purpose and the distribution of trip volumes by distance ranges come reasonably close to the observed values (see comparisons reported below). The purpose of this model estimation is to ensure that the distributions of journeys to work, education, business and other personal destinations are calibrated to represent the observed patterns. The zonal distribution of employed residents is constrained by MEPLAN in the model to the RSE-Beijing estimated values for 2010, which in turn conform to the zonal population census totals for 2010. As a by-product of this MEPLAN constraints process, zonal non-monetary attractiveness terms are estimated which represent other influences on employed resident locations than costs of living and generalised commuting costs. The main output of the land use and travel demand model for the strategic transport model is the trip matrices, which are converted from production-consumption matrices of journeys to work and monthly non-commuting travel to morning peak period OD matrices.

(d) Using the trip OD matrices from the above and the transport costs, times and generalised costs for each transport user mode based on the network coding (see below), the calibration of the mode choice model produces modal OD matrices that in summary form are reasonably close to the aggregate mode choice statistics that are reported in BTRC (2012). The journeys are attributed to different modes of transport that are available between each pair of locations, according to the modal choice behaviour of each socio-economic group. This is done by demand segment defined in terms of the socioeconomic group and purpose of travel. This simplified procedure is adopted because only aggregate mode choice statistics are currently available. The car and public transport costs are estimated through data collected from our field surveys.

(e) The network assignment model takes the trip OD matrices and assigns them to the road and rail (including metro) networks, using a discrete-choice-model based multipath assignment procedure.

(f) The modelled trips, trip-kms, mode choice profiles and demand elasticities are then compared with known value ranges and once the discrepancies between the modelled and observed values are deemed small enough, the iterations among (c), (d) and (e) will cease and the model outputs the simulation results at step (g). If not, the iterations continue back to (e), (d) and (c).

In **Figure 4.62**, whilst travel demand information is generated and fed top-down from module to module, the travel costs, times and generalised costs are transmitted bottom-up. This allows an extensive interaction between land use and transport. The model calibration procedure actually starts from network assignment model, and works its way back up to the land use and travel demand model, following the order in which the costs and generalised costs are estimated. The travel costs and generalised costs are also fed back to RSE-Beijing for the estimation of land use activity locations for 2010 and this can also be done for future year predictions, although this is beyond the scope of this dissertation (**Figure 4.63**). Note also that the current model includes morning peak modal choice and assignment only. However, the model structure allows it to be extended to cover other time periods of travel.

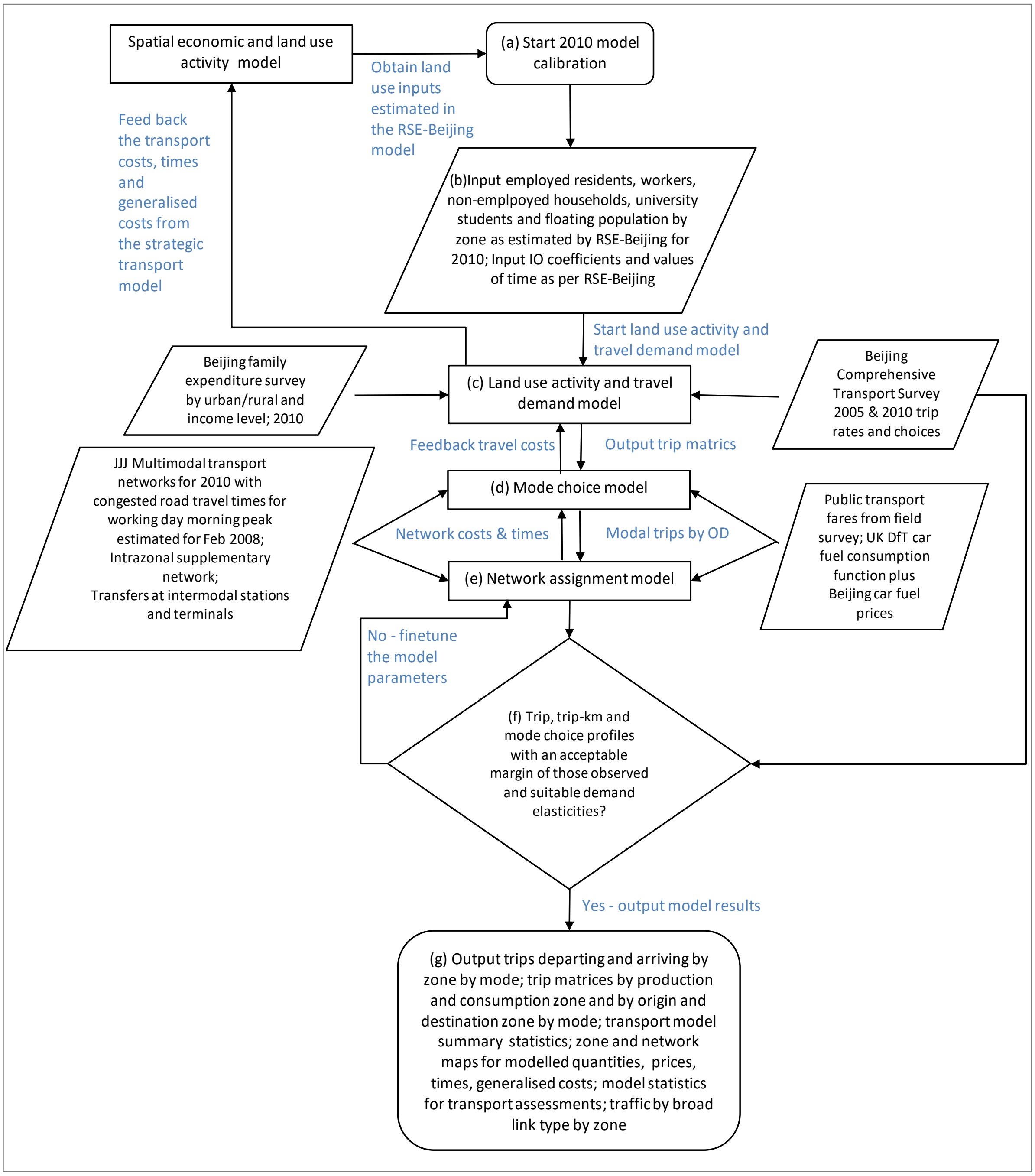


Figure 4.62. Summary of Model Calibration for 2010

<Note: JJJ stands for Jing-Jin-Ji (Beijing-Tianjin-Hebei), which covers the same area with the Greater Beijing Region>

Similarly, when the model is used in predictive mode for either a Base or a future year, the broad structure of data flows remains largely the same (**Figure 4.63**). There are the following steps to be taken for the predictive use of the model:

(h) The model starts with inputs from exogenous land use data from RSE-Beijing. The main reason for inputting the land use data this way is that RSE-Beijing has a more complete representation of the spatial and temporal economic and land use interactions and thus is capable of producing a more robust forecast of the location patterns for jobs, residents, housing and business floorspace;

(i) The inputs zonal levels of employed residents, workers, non-employed households, university students, and floating population by respective type by zone, and the input-output coefficients, household income levels, consumption patterns and values of time as adopted in RSE-Beijing;

(j) The MEPLAN land use and transport demand model are then run to produce both commuting and non-commuting travel matrices, and convert them into morning peak OD matrices;

(k) Using the trip matrices produced above, the mode choice model is run to produce modal trip matrices, using a specific set of transport costs, times and generalised costs as appropriate for a given policy scenario;

(l) The network assignment model is then run to assign the traffic to both inter- and intra-zonal multimodal networks, using the modal matrices produced above and the scenario inputs;

(m) The model predictions are subject to sense-check using any potentially relevant knowledge and model results from elsewhere, and also verified in terms of demand elasticities. If the results pass those checks, they are reported at step (n). If not, the test is revised and steps (j), (k) and (l) repeated. It is possible for the travel costs, times and generalised costs from the strategic transport model to feed back to RSE-Beijing, although this is beyond the scope of this dissertation.

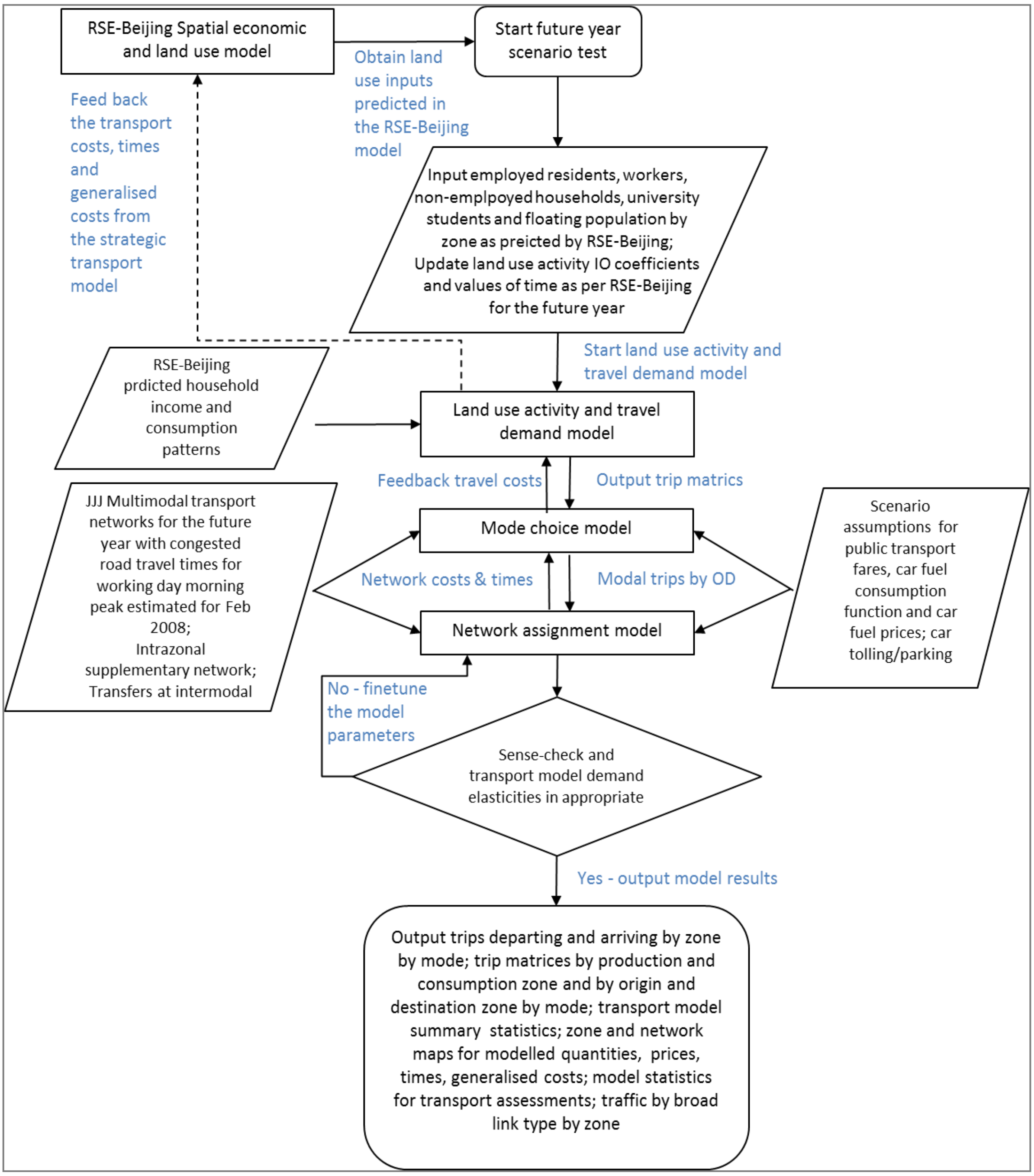


Figure 4.63. Summary of Model Predictive Use

<Note: JJJ stands for Jing-Jin-Ji (Beijing-Tianjin-Hebei), which covers the same area with the Greater Beijing Region>

4.8.1. The land use activity and travel demand model

The land use model consists of two broad economic sectors:

(1) The productive sector which represents all primary, manufacturing and service industries in the Study Area;
(2) The household sector, which acts both as a final consumer, with the households containing employed residents being a supplier of labour to the productive sector.

Within the model, each sector is composed by a number of activity segments and their demand for goods and services, floorspace and travel. These represent the production, consumption and trade within the city.

The productive sector consists of three types of jobs – high, medium and low income jobs – and their demand for labour is measured in employed and self-employed persons, the demand for commercial floorspace in which to locate and conduct the businesses, and the demand for travel on business.

The household sector, on the other hand, is represented by three types of employed and self-employed residents, their households, other unemployed and economically inactive households, university and college students and the floating population. The resident and floating population generates the demand for housing, consumer goods and services, delivery associated with the goods and services, the demand for personal travel to schools, shopping/personal business, leisure, and others. The demands are generated through either households or individual members as the units of consumer choices.

The model links the productive and the household sectors with **(a)** residents going to work as the employed workers, which provides the basis for simulating commuting journeys to/from work as well as the demand and supply of labour; **(b)** the households' demand for goods and services. The model estimates household demand for goods and services that are required in each zone, and the shopping trips generated (as part of non-work trips). It currently does not model the delivery of goods and services that are not brought back through shopping trips – this is because such deliveries are carried out outside the morning peak periods.

The basic units of measurements are cost in Fen (one cent of Yuan in 2010 prices), time in hours (for the time-based measurement of generalised travel cost). Households, employed persons, jobs and dwellings are also units used for the respective activities. Where temporal flows are involved (e.g. consumption by households) the temporal unit is one average working month (i.e. times in the year that exclude major national and local holiday periods).

The modelled land use activities and travel demands are segmented in line with RSE-Beijing (Jin et al, 2015; Rong, 2016):

(a) **The employed workers**: represent the workforces at floorspaces, including employed and self-employed residents living in households and collective establishments (the latter include migrants from the rest of China and abroad who have stayed in the Greater Beijing area for more than 6 months). The data is sourced from the 2008 China National Economic Census, and inflated to the 2010 totals using the National Population Census of 2010.
(b) **Employed residents**: the employed population at dwellings by three different socioeconomic groups (i.e. income level).
(c) **Employed households**: number of households with at least one employed or self-employed adult. The data is estimated in the model by the population of employed residents.
(d) **Non-employed households**: number of households with all members' economic statuses are inactive (e.g. unemployed and retired), and it is estimated based on the 2010 Population Census.
(e) **University and college students, floating population, non-employed residents, housing and business floorspace**: these activities are estimated in the RSE-Beijing calibration.
(f) **Non-commuting travel by purpose**: in line with BTRC (2012), include trips for three purposes, i.e. education (i.e. pre-university/college only), employers' business, and other personal travel.

The above demographic data covers all household and floating populations throughout the Greater Beijing area. In terms of the cross-boundary trips (between Beijing and external areas), it is worth noting that only inbound commuting trips (i.e. from the rest of China to Beijing) are considered. We assume that trips of outbound commuting and other purposes (both inbound and outbound) are negligible and hence not included in the model. The calibration and validation of the 2000 and 2010 RSE model are carried out and reported separately (Rong, 2016), and here we use the identical parameter values as the RSE model (**Table 4.27**).

Table 4.27. Segmentation of modelled land use activities and travel demand

No.	Description	Unit	Household Income Group	Code	Concentration Parameter* (Hour)
(a)	Employed worker	Employee	High	21	-
			Medium	22	-
			Low	23	-
(b)	Employed resident	Employee	High	31	0.071
			Medium	32	0.073
			Low	33	0.092
(c)	Employed Household	household	High	51	-
			Medium	52	-
			Low	53	-
(d)	Non-employed household	household	High	55	-
			Medium	56	-
			Low	57	-
(e)	College/university student	Headcount	-	28	-
	Floating population	Headcount	-	29	-
	Unemployed	Headcount	High	74	-
			Medium	79	-
			Low	84	-
			Non-employed	89	-
	Retired	Headcount	High	73	-
			Medium	78	-
			Low	83	-
			Non-employed	88	-
	Children aged 0-5	Headcount	High	70	-
			Medium	75	-
			Low	80	-
			Non-employed	85	-
	Children aged 6-17	Headcount	High	71	-
			Medium	76	-
			Low	81	-
			Non-employed	86	-
	Office floorspace	m^2	-	100	-
	Housing floorspace	m^2	-	101	-
	Retail floorspace	m^2	-	102	-
(f)	Journeys to school	trip	High	121	2.55
			Medium	122	2.55
			Low	123	2.55
	Other personal trips	trip	High	135	2.05
			Medium	136	2.05
			Low	137	2.05
	Business trips	trip	High	140	1.80
			Medium	141	1.80
			Low	142	1.80

*Note: <*The unit of the location disutility function is time in hour. The concentration parameter for location choice logit model may have different meanings between commuting trips and secondary trips. For commuting trips (model code 31-33), it represents the overall travel disutilities of a month of commuting of both home-to-work and work-to-home; while for secondary trips (model code 121-199), it means the disutility and living costs for monthly bidirectional single trips. Coefficient of 0.07 for commuting trips is equivalent to 0.07*44 (3.08) journey-to-work trips.>*

The resultant travel demand is verified through comparison against synthetic model outputs, such as the distribution (zone level) of employed residents, the average trip length by trip purpose and travel demand elasticities. The spatial distribution of employed residents is produced by MEPLAN embedded gravity model. We report the results of average trip lengths and travel demand elasticities as part of the verification of modal choice below.

4.8.2. Modal Choice and Network Assignment

The modal choice and network assignment are built upon a comprehensive representation of the multimodal transport network as presented above. The mode choice is simulated by a hierarchical multinomial logit model including intrazonal distance ranges and network assignment similarly by a multipath discrete choice assignment model. Both models are for a typical working day morning peak between 6:30-9:30am, and the basic units of measurements are: cost in Fen (one cent of RMB Yuan in 2010 prices), time in minutes, and capacity (for a 3 hour AM peak period) in pcu's on road, and in passenger on metro and rail.

After some experimentation with different structures at the calibration stage, the modal split hierarchy for passenger travel has eventually been represented with a flat logic model of discrete choice, as shown in **Figure 4.64**.

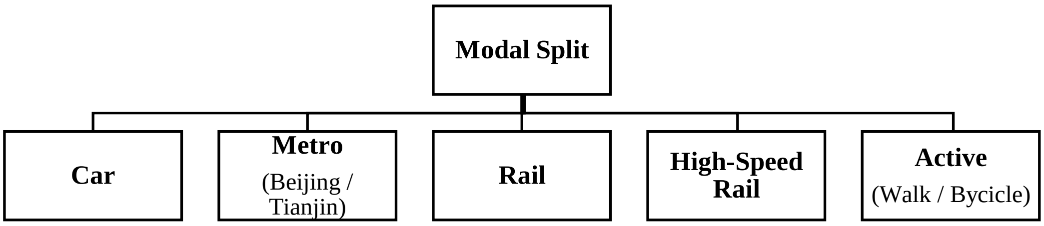


Figure 4.64. Modal split hierarchy

The model incorporates all the main modes, including walking and cycling as separate modes. For model calibration the estimated February 2008 congested speeds in the road network are used as a proxy for 2010 road speeds because observed 2010 road speeds are not available. Since the road space rationing measures to take out 1 in 5 cars in Beijing was put in place since late 2008 as a preventative measure for worsening congestion, road network congestion in Beijing did not worsen significantly till early 2012 when the new car purchase lottery was initiated. This means that the February 2008 congested speeds would be an acceptable proxy for those of 2010, with a likely bias of slightly underestimating road congestion.

We define the mode choice model by first define the segmentation of passenger travel demand. The same passenger travel demand segmentation as in the land use and travel demand module is adopted, i.e. by income level by trip purpose (as the parameters in **Table 4.28**, so as in UTF). Since the levels of car ownership closely correlate with the income level across the Greater Beijing area including the dense urban areas, no further car ownership segmentation is required for model calibration in 2010 (such as implemented in the LASER model, see Jin and Williams, 2002). In any case there is currently no direct data to differentiate car ownership levels now or in the near future. In the event that high income households would be restrained in terms of car ownership in a future year (which, given the current trends of development, may likely to be implemented sometime in the future), the lack of differentiation of car ownership levels within the high income group may lead to an overestimation of car travel demand in the dense urban areas such as central Beijing. We will return to this discussion in **Chapter 5**.

All main transport modes defined in two steps. They include all main modes used for road and rail travel in the study area. In MEPLAN terminology these main modes are called *user modes* and may include distinct travel stages using different *network modes.* For instance, travel on main mode 'Surface Rail' may involve network modes such as: access and waiting at a rail station, riding the train, egress, and access trip destination, etc. For ease of model implementation, the intrazonal modes are defined separately from the inter-zonal modes, and are subdivided by distance ranges for the hierarchical multinomial logit model. The MEPLAN network modes and user modes are presented respectively in **Table 4.29** and **Table 4.30**.

Table 4.28. Segmentation of travel demand

Trip Purpose	Unit	Income Group	Model Code	Modal choice concentration Parameter		Marginal utility of money* (Fen/minute)
				Interzonal	Intrazonal	
Commuting trips	Person	High	1	0.06	0.10	0.046877
		Medium	2	0.07	0.11	0.095804
		Low	3	0.08	0.12	0.174834
Education trips	Person	High	4	0.06	0.10	0.046877
		Medium	5	0.07	0.11	0.095804
		Low	6	0.08	0.12	0.174834
Employers' business trips	Person	High	7	0.04	0.08	0.023439
		Medium	8	0.05	0.09	0.047902
		Low	9	0.06	0.10	0.087417
Other personal trips	Person	High	10	0.06	0.10	0.046877
		Medium	11	0.07	0.11	0.095804
		Low	12	0.08	0.12	0.174834

<*Note: *Marginal utility of money is reciprocal for values of time, and the unit Fen is one cent of Yuan*>

Table 4.29. Definition of network modes

Model code	Name	Unit	Use network links
10	Interzonal car	pcu	Interzonal road network
20	Interzonal bus	person	
30	Interzonal walk	person	
40	Interzonal cycle	person	
50	Interzonal rail	person	Interzonal rail/metro/light/high-speed rail networks
60	Interzonal metro/light rail	person	
70	High Speed Rail	person	
84	Transfer between modes	person	Intermodal transfer links
91	Feeder car	pcu	Interzonal road network
92	Feeder bus	person	Interzonal road network
93	Feeder walk	person	Interzonal road network
94	Feeder cycle	person	Interzonal road network
95	Feeder metro/light rail	person	Interzonal metro/light rail networks
101-109	Intrazonal cars for distance band 1-9	pcu	Intrazonal road/ rail/metro/light rail networks by distance range
111-119	Intrazonal bus for distance band 1-9	pcu	
121-123	Intrazonal walk for distance band 1-3	pcu	
131	Intrazonal cycle for distance band 1-5	pcu	
141	Intrazonal metro for distance band 1-9	pcu	

Table 4.30. Definition of user modes

Model code	Name	Unit	Value of time multiplier
1	Car	Passenger	1.00
2	Bus	Passenger	1.25
3	Walk	Passenger	1.00
4	Cycle	Passenger	1.00
5	Rail	Passenger	1.00
6	Metro	Passenger	1.00
7	High Speed Rail (HSR)	Passenger	1.00
8-10	Intrazonal walk for distance range 1-3	Passenger	1.00
11-19	Intrazonal car for distance range 1-9	Passenger	1.00
21-29	Intrazonal bus for distance range 1-9	Passenger	1.25
31-39	Intrazonal rail/metro/light rail for distance range 1-9	Passenger	1.00
41-45	Intrazonal cycle for distance range 1-5	Passenger	1.00

The user mode specific constants are defined for metro and cycle for both interzonal and intrazonal as summarised in **Table 4.31**.

Table 4.31. User mode specific constants (interzonal)

Flow			User mode specific constants (minutes)						
Code	Purpose	Income Group	Car	Bus	Cycle	Walk	Metro	Rail	HSR
1	Commuting	High	0	0	18	0	-10	0	0
2		Medium	0	0	16	0	-10	0	0
3		Low	0	0	16	0	-10	0	0
4	Education	High	0	0	18	0	-10	0	0
5		Medium	0	0	16	0	-10	0	0
6		Low	0	0	16	0	-10	0	0
7	Employers' business	High	0	0	22	0	-10	0	0
8		Medium	0	0	22	0	-10	0	0
9		Low	0	0	20	0	-10	0	0
10	Other personal	High	0	0	18	0	-10	0	0
11		Medium	0	0	16	0	-10	0	0
12		Low	0	0	16	0	-10	0	0

In this thesis, the modelling of transport modes is focused on the modal choice in the strategic transport model. Since observed data from Beijing is only available in aggregate tables and cannot allow the showing of the fit of the interzonal and intrazonal results respectively, we have to combine the two when calibrating the model. It is also worth noting that the Year 2000 run results were used in the calibration of RSE model (Jin et al, 2013; Wan, 2016; Rong, 2016), but not this transport model. In addition, data for calibration is sparse, so we used trial-and-error method to calibrate the model, and also assisted by the magnitude of parameters from the Greater London Model (Jin et al, 2002) such as the user mode specific constants for both interzonal and intrazonal as summarised in **Table 4.30** and **Table 4.31**.

The car operating cost function is derived from the latest UK DfT (Department for Transport) car fuel consumption function (given that the car fleet in the Greater Beijing area is just as modern as in the UK) and the retail petrol price for 2010 (there are very few diesel cars). The car operating cost function is a standard multinomial function of distance and vehicle link speed which is sensitive to the changes in road speeds. For bus and metro, the tariff information from Beijing were collected in 2013, which were unchanged from 2010.

Several stages were involved in calibrating modal split and assignment:

(a) First of all, the modal networks were tested in terms of minimum paths (see **Section**). The distances, costs, and times between key origin and destination zones were checked against data samples from Google Maps Direction service and field measurements;

(b) A wide range of parameters were tested for the logit-based path choice model for road path choice. Since there is no empirical data to use in a formal parameter estimation, the test runs were compared in terms of the extent of the multi-path spread under different parameters. A value was chosen for car and bus travel on the basis that it generated reasonably concentrated path choices along inter-urban corridors, and at the same time gave a fairly wide path spread within the urban areas at the origin and destination. For bus, this is to simulate the effect of a spread of alternative bus routes between an origin and a destination, rather than to represent any single bus taking different routes. For coach, underground and rail, the least time route is chosen on the assumption that for the AM peak, passengers make the fastest route their choice through scheduled services;

(c) A full set of cost and time matrices were generated by mode, using this road assignment model. The time matrices include the effects of congestion on road as represented by the Feb 2008 congested speeds;

(d) On the basis of these cost and time matrices, an interzonal modal split calibration was carried out, using observed aggregated modal choices by trip purpose and distance bands as reported by BTRC (2012). A number of possible formulations of the generalised cost function were tested, particularly regarding the valuation of time multipliers on car, bus, train and access/transfer stages of travel;

(e) Also, an intrazonal distance range and mode choice parameter estimation were carried out, using mode choice by distance range data given in BTRC (2012).

Since the detailed mode choice data by location OD is not available, it is not feasible to carry out a model choice model parameter estimation through formal procedures such as maximum likelihood maximisation. However, observed mode choice patterns have been reported in a number of aggregate dimensions and an optimisation procedure has been set up to fine-tune the model parameters using the modelled zonal modal matrices subject to minimising the errors between the modelled outturn summary statistics and the observed aggregate data. The parameter value estimation is summarised as follows.

(a) The values of time are fixed *a priori* for each travel demand segment. These values of time are based on the travellers' household income levels. These values of time are used to combine money cost and travel time into a generalised travel cost before the model parameter estimations were carried out. This is because there are sound theoretical reasons to determine the values of time based on income levels based on international values of travel time studies and fixing the values of travel time a priori considerably simplifies the parameter estimation task.

(b) Different multipliers on the travel time on car, bus, rail and access/intermodal transfer were tested, ranging from 1.5 to 0.5. The final multipliers on the values of time are reported in **Table 4.30**.

(c) Distinct modal access and egress times at respectively origin and destination zones have been set up based on our field survey (**Table 4.32**). The differentiated zonal access and egress times are included in the modal choice models to represent different conditions of access and, where applicable, parking.

(d) The bus modal constant is set to zero, whilst modal constants were estimated for the other modes in the optimisation procedure.

This thesis is focused on strategic transport mode. For details of RSE model calibration, as in step (b), (d) and (e) (Wan, 2016; Rong, 2016). The year 2000 run results were used in the calibration of RSE model, but not this transport model. In addition, data for calibration is sparse, so we used trial-and-error method to calibrate the mode, and also assisted by understanding the London Model. Due to the unavailability of separate dataset, it is not possible to show inter-zonal and intra-zonal parameters respectively.

Table 4.32. Origin and destination access/egress times by zone area (minutes/trip)

Zone area	User modes											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8-10**	**11-19**	**21-29**	**31-39**	**41-45**
Beijing Central 4 districts	10	15	0	5	10	15	30	0	10	10	10	5
Beijing Suburban 4 districts	10	15	0	5	10	15	30	0	10	10	10	5
Hebei zones around Beijing	10	15	0	5	10	15	30	0	10	10	10	5
Hebei zones nearby Beijing	10	15	0	5	10	15	30	0	10	10	10	5
other Beijing zones within 6th	10	20	0	5	10	15	30	0	10	10	10	5
the rest of Beijing	10	20	0	5	10	15	30	0	10	10	10	5
the rest of China	10	15	0	5	10	15	30	0	10	10	10	5
the rest of Hebei	10	15	0	5	10	15	30	0	10	10	10	5
the rest of Tianjin	10	15	0	5	10	15	30	0	10	10	10	5
Tianjin Central	10	15	0	5	10	15	30	0	10	10	10	5
Tianjin Suburban zones	10	20	0	5	10	15	30	0	10	10	10	5

<Note: The origin and destination times are equal to the values presented above.>

In the following we give a summary of the comparison of the calibrated 2010 model results with the observed 2010 values available from BTRC (2012) for the zones in Beijing within the sixth ring road. The BTRC (2012) data for within the sixth ring road is the only systematic information available in the Greater Beijing area. Although this area is the most challenging for model estimation given its complexities in land use, interactions among urban activities, the verification we carry out here does not cover the whole of the Greater Beijing area. More verification would be required for the rest of the Greater Beijing area and at a finer level of geographical detail if and when new survey data emerges in the future.

Figure 4.65 first presents the overall trip length distribution over the morning peak. The Modelled trips are slightly more concentrated in the distance ranges <10km. Since the BTRC data does not include the travel by the floating population, which are more concentrated in the core urban area, this discrepancy is to some extent reasonable. On the whole, the model is able to reproduce the observed distance range profile. **Figure 4.66** presents the overall morning peak mode shares. Again, the model is capable of reproducing the broad mode share pattern with a slight over-estimate of car, bus and rail and an under-estimate of walk and cycle. Note that in 2010, the shares for car, bus and walk are almost equal, which is a feature that resulted from a rapid rise in car share and falls of bus (BTRC, 2012); the share for walk has persisted for the existence of a large number of short non-commuting trips in the area (BTRC, 2012).

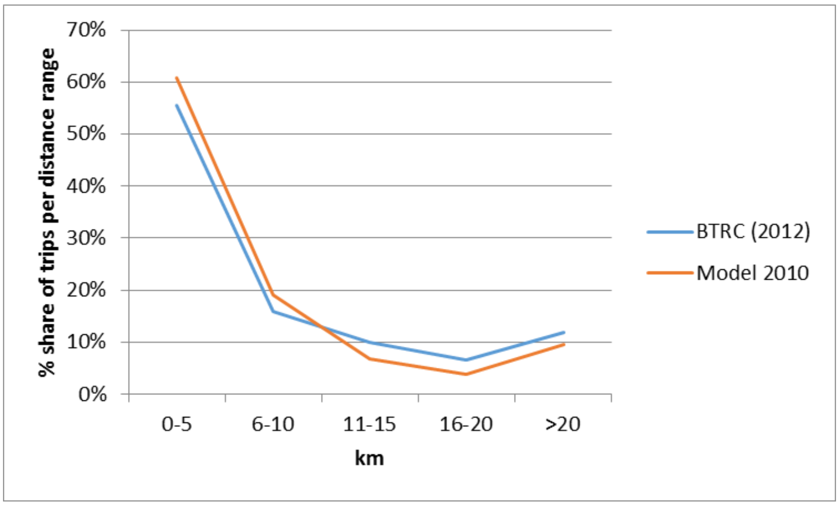


Figure 4.65. Trip length distribution: modelled trips (2010) vs. BTRC trips (2012)

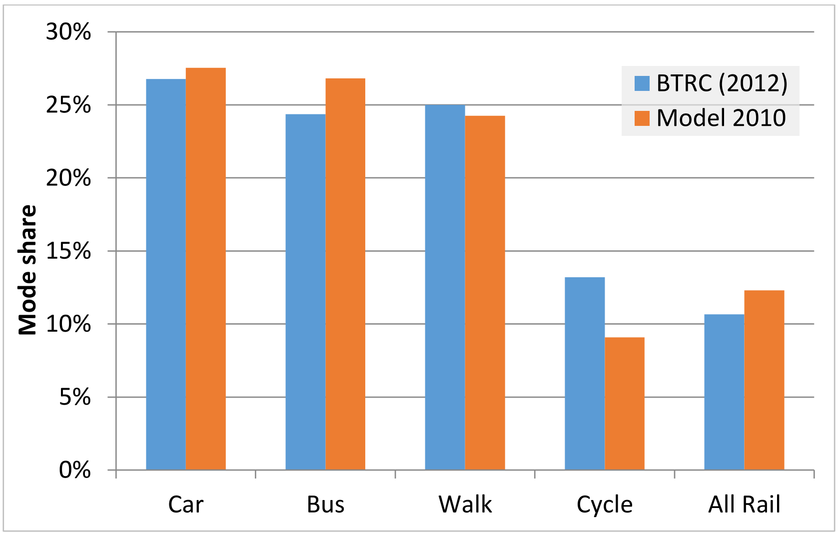


Figure 4.66. Comparison of modelled and observed % mode share, 2010

Table 4.33 (a) and **(b)** provide further details of the comparisons by distance range, and **Table 4.34** of the mode shares by trip purpose, against the observed data reported in BTRC (2012). The comparisons show that the model is capable of capturing the broad patterns of the choices for all modes and distance bands, although there are indeed many discrepancies that can be further improved in the future works. Arguably those improvements would be more effectively done when more detailed observed data is available, such that the model could be calibrated using a formal numerical optimisation method such as maximum likelihood. We have further compared the average trip lengths (7.3km for the modelled vs 7.6km as reported by BTRC, 2012), and average travel times for commuting (46.4 minutes modelled vs 45.0 observed) and for school education (34.8 minutes modelled vs 34.0 observed).

Table 4.33. Modal split: Modelled vs. Survey (2010)

(a) Total percentage of each distance band column is 1

Mode	Distance	0-5km	6-10km	11-15km	16-20km	>20km	Total
Car	Survey	19.3%	41.5%	42.6%	44.6%	43.7%	26.8%
	Modelled	29.2%	28.7%	24.3%	26.6%	17.4%	27.5%
Bus	Survey	14.8%	36.3%	32.7%	29.0%	27.3%	24.4%
	Modelled	16.6%	57.1%	49.1%	28.1%	14.8%	26.8%
Walk	Survey	49.1%	2.1%	1.1%	0.8%	0.9%	25.0%
	Modelled	39.7%	0.8%	0.1%	0.0%	0.0%	24.3%
Cycle	Survey	15.6%	9.3%	2.8%	1.6%	0.5%	13.2%
	Modelled	13.5%	3.9%	1.5%	0.4%	0.0%	9.1%
Rail/Metro	Survey	1.3%	10.8%	20.8%	24.2%	27.6%	10.7%
	Modelled	1.0%	9.5%	25.0%	44.8%	67.8%	12.3%
Total	Survey	100.1%	100.0%	100.0%	100.2%	100.0%	100.0%
	Modelled	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

(b) Total percentage of each model row is 1

Mode	Distance	0-5km	6-10km	11-15km	16-20km	>20km	Total
Car	Survey	32.5%	22.0%	15.1%	9.7%	20.7%	100.0%
	Modelled	64.4%	19.8%	6.0%	3.8%	6.0%	100.0%
Bus	Survey	31.5%	29.3%	17.0%	10.3%	11.9%	100.0%
	Modelled	37.6%	40.5%	12.5%	4.1%	5.2%	100.0%
Walk	Survey	98.1%	1.2%	0.3%	0.2%	0.2%	100.0%
	Modelled	99.4%	0.6%	0.0%	0.0%	0.0%	100.0%
Cycle	Survey	80.4%	14.7%	3.2%	1.4%	0.3%	100.0%
	Modelled	90.5%	8.2%	1.2%	0.2%	0.0%	100.0%
Rail/Metro	Survey	4.9%	15.7%	20.3%	19.2%	39.9%	100.0%
	Modelled	5.1%	14.7%	13.9%	14.2%	52.1%	100.0%
Other	Survey	23.9%	16.9%	18.3%	11.4%	29.5%	100.0%
	Modelled	-	-	-	-	-	-
Total	Survey	55.5%	15.9%	10.0%	6.7%	11.9%	100.0%
	Modelled	60.8%	19.0%	6.8%	3.9%	9.5%	100.0%

Note: <Rail mode includes metro, light rail, rail and high-speed rail (where applicable); Other mode includes all other transport modes, such as company shuttle>

Table 4.34. Trip purpose split: modelled vs. survey (2010)

Purpose / Mode	Commuting		Education		Business		Other		All Together	
	Survey	**Modelled**	**Survey**	**Modelled**	**Survey**	**Modelled**	**Survey**	**Modelled**	**Survey**	**Modelled**
Car	26.2%	26.6%	16.3%	23.9%	72.0%	55.8%	26.0%	28.3%	27%	28%
Bus	25.7%	26.7%	32.0%	33.8%	11.0%	14.5%	23.0%	25.9%	24%	27%
Walk	19.4%	19.4%	32.6%	25.8%	3.0%	12.0%	29.0%	28.8%	25%	24%
Cycle	14.8%	9.3%	13.7%	11.9%	3.0%	3.5%	13.0%	8.5%	13%	9%
Rail/Metro	13.9%	18.0%	5.4%	4.6%	11.0%	14.1%	9.0%	8.6%	11%	12%

Note: <Rail mode includes metro, light rail, rail and high-speed rail (where applicable); Other mode includes all other transport modes, such as company shuttle>

4.8.3. Travel demand elasticity tests

The tests of outturn travel demand elasticities can be considered an important part of model validation in two senses. Firstly, travel demand elasticities are not input as a piece of observed data for model calibration. Secondly, for future year scenario tests, the modelled demand responses to changed scenario inputs (e.g. transport cost and time changes) are in most cases even more important than the goodness-of-fit in the Base Year. As there are no established travel demand elasticities for the Greater Beijing area, our test here will be based on international experience.

We carry out model elasticity tests by fixing the total trips (i.e. over all modes) between every OD for each trip purpose and demand segment, and test the responses of the model in terms of modal shifts only on each OD – this can be considered a short term elasticity test, which can then be compared with the short term elasticities as found in the UK by the UK DfT (see WebTAG.org).

We carry out tests on both travel cost and travel time elasticities. Because in the Greater Beijing area the income levels are expected to rise fairly rapidly in spite of the recent slowdown in economic growth rates, and the demand elasticities are expected to reduce as the income levels rise, we test the elasticities for both 2010 and our future planning horizon 2030. We test the model by increasing the travel cost or travel time of a single user mode by 20% across the whole study area.

Table 4.35 summarises the car cost and time elasticities for 2010 and 2030 by flow group and area. As expected, at the relatively low-income levels of 2010, the car cost elasticities are fairly high. It is higher for commuting and education trips where non-car modes are often good alternatives, lower for other personal trips, and lowest for employers' business trips. The cost and time elasticities tend to be higher in central urban areas where alternative mechanised modes are better available; the cost elasticities are also higher in low income areas such as Hebei. As expected, as the income and valuation of time rises from 2010 to 2030, the cost elasticities are substantially reduced.

Table 4.35. Car cost and time elasticities for travel 2010 and 2030 by travel demand group and area

Area	Travel demand group	2010 Car cost up 20%	2010 Car time up 20%	2030 Car cost up 20%
Central Beijing	Commuting	-1.41159	-0.52606	-0.83192
	Education	-1.30512	-0.57353	-0.29675
	Business	-0.63849	-0.50546	-0.09245
	Other personal	-0.99128	-0.48865	-0.39913
	All	-0.80441	-0.51296	-0.37623
Suburban Beijing	Commuting	-1.20379	-0.4748	-0.34117
	Education	-0.9217	-0.35819	-0.15447
	Business	-0.40282	-0.31838	-0.04395
	Other personal	-0.74639	-0.36624	-0.37586
	All	-0.67026	-0.38937	-0.1794
Other Beijing areas inside the sixth ring road	Commuting	-1.47339	-0.45366	-0.6786
	Education	-0.79825	-0.27553	-0.20149
	Business	-0.4593	-0.24603	-0.05421
	Other personal	-0.75993	-0.32306	-0.20415
	All	-0.84153	-0.3508	-0.44006
Rest of Beijing	Commuting	-1.91267	-0.47802	-1.16643
	Education	-0.87556	-0.24577	-0.38894
	Business	-0.6559	-0.20724	-0.1107
	Other personal	-0.89183	-0.34149	-0.29673
	All	-1.24985	-0.36655	-0.96217
Central Tianjin	Commuting	-1.03088	-0.33914	-0.26309
	Education	-0.68771	-0.26928	-0.1552
	Business	-0.32282	-0.13785	-0.19542
	Other personal	-0.7969	-0.34032	-0.52381
	All	-0.36021	-0.15279	-0.20853
Suburban Tianjin	Commuting	-1.25403	-0.52714	-0.1888
	Education	-1.02837	-0.35833	-0.16205
	Business	-0.32545	-0.19792	-0.08304
	Other personal	-0.81807	-0.4794	-0.27785
	All	-0.37514	-0.22168	-0.09499
Rest of Tianjin	Commuting	-1.35468	-0.28164	-1.89176
	Education	-1.02031	-0.30085	-0.49445
	Business	-0.60251	-0.2279	-0.20764
	Other personal	-1.03691	-0.46497	-0.37407
	All	-0.637	-0.23915	-0.29386
Hebei areas near Beijing	Commuting	-1.18915	-0.26318	-1.70858
	Education	-0.94568	-0.29045	-0.41003
	Business	-0.60107	-0.20445	-0.11884
	Other personal	-0.9808	-0.43355	-0.22543
	All	-0.63398	-0.21699	-0.30033
Hebei areas around Beijing	Commuting	-3.21758	-1.73492	-1.60566
	Education	-1.6517	-1.55589	-1.246
	Business	-0.84158	-1.26407	-0.48263
	Other personal	-1.88042	-0.92659	-0.74678
	All	-1.01676	-1.29882	-0.67221
Rest of Hebei	Commuting	-0.5839	-0.19069	-1.25059
	Education	-0.41549	-0.16262	-0.38629
	Business	-2.59311	-0.0734	-0.04756
	Other personal	-0.84756	-0.28035	-0.8125
	All	-1.10902	-0.08958	-0.17447

Table 4.36 summarises the cost and time elasticities in 2030 which are particularly important for policy scenarios tests for travelling by car, bus and metro for each demand segment. By 2030, whilst the high-income group has cost elasticities of -0.30 to -0.40 for car travel, which

approaches the level expected in developed countries, the overall demand elasticities are still going to be as low as -0.60 to -0.70. The bus and rail cost elasticities are not as high as in the developed countries, particularly for the higher income groups, as those who are dependent on travelling by public transport do not tend to have many other options (although we assumed that all travellers of any income group can access to car due to the lack of household car ownership data, the relatively high costs of car/highway trips could prevent low-income travellers from choosing car mode). We note the relatively high bus and rail time elasticities, which imply that the travelling public are very sensitive to the time taken by public transport. It is also worth noting that the public transport cost elasticities are much lower than the bus/rail time elasticities. This is mainly due to the fact that the public transport fares are kept very low in Beijing (e.g. the ticket price in 2010 are 1 Yuan flat for bus journeys and 2 Yuan flat for metro) and hence they forms only a minuscule component of the generalised travel costs in the model.

Table 4.36. Cost and time elasticities 2030: by travel demand segment and user mode

Segment Code	Segment Name	Car cost up 20%	Car time up 20%	Bus cost up 20%	Bus time up 20%	Rail/Metro cost up 20%	Rail/Metro time up 20%
1	Commuting trips, high income household	-0.40	-0.77	-0.02	-2.73	-0.10	-1.61
2	Commuting trips, medium income household	-1.10	-1.11	-0.07	-2.87	-0.17	-1.54
3	Commuting trips, low income household	-1.51	-1.09	-0.30	-2.93	-0.18	-1.03
4	Education trips, high income household	-0.39	-0.83	-0.05	-2.52	-0.14	-1.99
5	Education trips, medium income household	-0.93	-1.13	-0.17	-2.60	-0.26	-1.95
6	Education trips, low income household	-1.57	-1.35	-0.60	-2.51	-0.45	-1.98
7	Employers’ business trips, high income household	-0.29	-0.38	0.00	-2.45	-0.02	-0.88
8	Employers’ business trips, medium income household	-0.27	-0.24	0.00	-2.82	-0.09	-1.61
9	Employer’ business, low income household	-0.58	-0.33	-0.02	-3.13	-0.20	-1.91
10	Other personal trips, high income household	-0.30	-0.90	-0.02	-2.55	-0.12	-1.71
11	Other personal trips, medium income household	-0.51	-0.98	-0.06	-2.73	-0.23	-1.96
12	Other personal trips, low income household	-0.69	-0.96	-0.16	-2.94	-0.51	-2.45
	All	**-0.63**	**-0.95**	**-0.08**	**-2.77**	**-0.20**	**-1.68**

Note: <Rail mode includes metro, light rail, rail and high-speed rail (where applicable); Other mode includes all other transport modes, such as company shuttle>

Finally, **Table 4.37** compares the short term model elasticities with the headline benchmark data from the UK for car and public transport costs. It confirms that car cost elasticities in the

Greater Beijing will still be substantially higher than in the UK, and demand management measures through pricing, if feasible for implementation, could achieve relatively large reductions in car use. On the other hand, PT cost elasticities are likely to be significantly lower than in the UK, which implies that a large percentage of the travelling public will continue to depend on PT as their main options of urban travel.

Table 4.37. Comparison of model results vs benchmark data (short term elasticities)

	Benchmark data for the UK		**Model elasticities on passenger kms Greater Beijing area for 2030**	
	Range for passenger-km	**Central value**	**PT fares (on 20% rise)**	**Car Fuel Price (on 20% rise)**
PT fares	-0.16 to -0.65	-0.30	-0.08 to -0.20	
Car fuel price	-0.07 to -0.28	-0.125		-0.63

Notes: <
1) The modelled figures are calculated based on percentage change in passenger-km divided by percentage change in PT fares or car fuel price;
2) PT includes bus, surface rail, metro and tram;
3) The UK benchmark data comes from Jin and Williams (2002).>

4.9. Summary

In this chapter, we demonstrate the collection of model input data and the validation of the data in the case study area – the Greater Beijing Region. The 221 zones in the regions covers the entire Chin. Within Beijing and Tianjin, the zones are divided on the basis of district boundaries; and outside the Greater Beijing Region, the zones are carved up by the municipal or provincial boundaries. Three staged sets (Base Year, Calibration Year, and Future Year) of transport networks are built, and those networks each consist of road networks (urban major and expressway), urban metro networks (in Beijing and Tianjin), railway networks (ordinary railway and high-speed railway), access links which connects different networks, and the intra-zonal links which are used to represent the activities within each model zone.

The microscopic analyses of the taxi GPS data shed lights on two prospects: firstly, the spatial-temporal DBSCAN cluster analyses provide insights into wider characteristics of road traffic in a way that have not been possible in the past; the estimation of congested link speed became much more efficient and precise in comparison of the conventional survey method. The GPS data we have used is low-frequency and it lacks any information about passengers, but after so many years it still remains the only vehicle GPS dataset that is available in Beijing. The hotspot analysis has indeed confirmed that the data, although lack of sufficient documentation when released online, reflects well the congestion patterns that was observed for that period. Based on this knowledge we have proceeded to using it for the estimation of congested road speeds. Through a novel algorithm we have been able to estimate the road speeds in the congested morning peak period in Beijing, which is then validated and will provide the essential input data for transport demand model calibration.

5. Model Applications

This chapter proceeds with model applications, with a particular focus upon the new approach to exploring the future patterns of travel demand and the likely magnitudes of requirements for infrastructure investment, regulation and pricing. This approach is in a sense the opposite to how strategic transport models are conventionally applied in assessment practice. The main reason why we explore this approach is that we expect between 2010 and 2030, in spite of the recent slowdown in national economic growth, travel demand (especially that for car travel) is likely to surge significantly along with income growth and a large number of residents moving into the high and medium income groups in the Greater Beijing area. The transition is likely to involve a non-marginal change in travel demand, which would be inappropriate to investigate using an approach for marginal transport improvements. Of course the structure of the strategic transport model also allows it to be applied to study marginal and small incremental transport improvements.

The approach we adopt first assumes that the residents in the city would demand a certain level of service from the urban transport system in terms of travel time, and work out what the jobs and residents location patterns will be given the changes in city size, income levels, expected lifestyle changes etc. The strategic transport then takes the location predictions to work out what the patterns of travel demand will be and how much pressure different parts of the transport will be under, in different investment, regulation and pricing sceanrios. We expect that this analysis will shed a new light on the impacts of transformations of the economy, demography, lifestyles and travel demand, and thus would help to fill the gap regarding the medium to long term vision for the design of a sustainable transport system for emerging economy cities such as Beijing. Because the policy interest is the strongest for the urban areas within the sixth ring road of Beijing, the data analysis below presents the results only for this area. Other areas in the Greater Beijing region can be analysed analogously.

In this chapter we first presents in **Section 5.1** the format of data analysis using the model outputs from the 2010 Base Year model run. To facilitate an overview of the model outputs, we summarise the model results first by travel demand segment and mode. We further summarise the results into the headline numbers by trip purpose and mode. In **Section 5.2** we examine the patterns of travel demand changes by comparing the 2030 reference case with 2010. We then investigate the effects of a range of strategic transport interventions through model tests for the short term (where the total flows are fixed on each OD zone pair; see **Section 5.3**) and the medium term (where the zonal totals of jobs and resident households are fixed; see **Section 5.4**).

in **Section 5.5** we assess the road capacity extension between 2010 and 2030. We then summarise the insights from the model tests in **Section 5.6**.

5.1. Result from the 2010 modal choice model

This section examines the results of the model in 2010.

Table 5.1. Summary by travel demand segment and mode: 2010

Demand segment	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	All	10.0	256.4	45.8	13.1	1,403	13,997
	Car	8.5	419.8	39.0	13.0	549	4,647
	Bus	6.7	100.7	45.3	8.9	308	2,062
	Walk	1.4	0.0	19.1	4.5	162	232
	Cycle	2.9	0.0	27.9	6.2	65	190
	Metro/rail	21.5	308.1	75.3	17.1	320	6,866
2	All	8.7	133.5	44.4	11.7	4,559	39,435
	Car	4.4	207.8	34.7	7.7	1,226	5,433
	Bus	8.3	100.8	48.9	10.2	1,268	10,511
	Walk	1.5	0.0	19.8	4.5	822	1,231
	Cycle	2.8	0.0	27.5	6.2	392	1,116
	Metro/rail	24.9	265.5	83.2	17.9	850	21,144
3	All	8.4	82.2	42.5	11.8	1,920	16,092
	Car	3.2	137.4	32.3	5.9	321	1,014
	Bus	11.4	101.1	56.5	12.1	528	6,012
	Walk	1.6	0.0	21.1	4.6	543	874
	Cycle	3.2	0.0	29.5	6.5	279	891
	Metro/rail	29.3	242.2	87.0	20.2	249	7,302
4	All	4.9	134.7	36.4	8.1	232	1,144
	Car	4.7	242.5	36.4	7.8	79	370
	Bus	5.5	100.6	41.1	8.0	78	429
	Walk	1.4	0.0	18.6	4.5	42	59
	Cycle	2.5	0.0	25.6	5.8	16	40
	Metro/rail	14.5	255.8	69.5	12.5	17	246
5	All	4.2	84.1	33.9	7.4	1,202	5,058
	Car	3.3	159.3	33.9	5.8	287	942
	Bus	5.9	100.6	42.1	8.4	420	2,465
	Walk	1.4	0.0	19.3	4.5	299	434
	Cycle	2.6	0.0	26.2	6.0	140	364
	Metro/rail	15.4	235.5	70.2	13.2	55	853
6	All	3.6	47.4	30.8	7.0	245	886
	Car	2.3	105.9	31.7	4.4	35	82
	Bus	6.7	100.7	44.3	9.1	69	466
	Walk	1.5	0.0	20.3	4.5	92	141
	Cycle	2.7	0.0	26.9	6.1	45	122
	Metro/rail	16.9	218.0	71.8	14.1	4	76
7	All	34.0	575.5	65.0	31.4	38	1,299
	Car	18.8	842.3	47.0	24.0	23	423
	Bus	6.1	100.6	44.0	8.3	4	27
	Walk	1.6	0.0	21.2	4.5	4	6
	Cycle	3.2	0.0	29.7	6.5	1	3
	Metro/rail	128.5	391.4	171.9	44.8	7	840
8	All	10.2	310.8	44.2	13.8	155	1,580
	Car	9.1	439.1	40.0	13.7	89	814
	Bus	8.0	100.8	48.1	9.9	22	172
	Walk	1.6	0.0	21.4	4.6	17	28
	Cycle	2.9	0.0	28.2	6.3	5	16
	Metro/rail	25.3	320.4	79.6	19.1	22	550
9	All	7.6	176.9	41.7	10.9	45	344
	Car	5.4	258.1	36.2	8.9	22	116
	Bus	9.6	101.0	51.5	11.2	9	83
	Walk	1.7	0.0	22.0	4.6	7	13
	Cycle	3.0	0.0	28.5	6.3	2	6
	Metro/rail	23.1	285.6	79.6	17.4	5	127
10	All	7.7	166.1	40.4	11.4	1,424	10,943
	Car	9.0	313.2	39.4	13.7	456	4,088
	Bus	6.2	100.6	43.0	8.6	404	2,489
	Walk	1.6	0.0	21.6	4.6	302	498
	Cycle	2.7	0.0	26.7	6.0	81	216
	Metro/rail	20.2	292.7	74.2	16.3	181	3,652
11	All	6.5	102.6	37.9	10.3	5,700	37,061
	Car	7.0	186.0	37.4	11.2	1,626	11,308
	Bus	7.0	100.7	45.1	9.3	1,524	10,668
	Walk	1.7	0.0	22.4	4.6	1,579	2,716
	Cycle	2.7	0.0	27.0	6.1	477	1,308
	Metro/rail	22.3	260.5	77.6	17.3	495	11,061
12	All	5.0	57.9	34.3	8.8	1,504	7,536
	Car	5.3	115.9	35.6	8.9	364	1,920
	Bus	8.8	100.9	49.4	10.6	306	2,677
	Walk	1.8	0.0	23.4	4.6	600	1,084
	Cycle	2.9	0.0	27.6	6.2	172	494
	Metro/rail	21.9	228.0	78.0	16.8	62	1,359

Table 5.2. Summary by trip purpose and mode: 2010

Demand segment	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	All	8.8	142.9	44.2	12.0	7,882	69,524
	Car	5.3	252.6	35.5	9.0	2,095	11,094
	Bus	8.8	100.9	50.2	10.5	2,105	18,585
	Walk	1.5	0.0	20.2	4.5	1,527	2,337
	Cycle	3.0	0.0	28.3	6.3	736	2,197
	Metro/rail	24.9	271.0	82.1	18.2	1,419	35,312
School	All	4.2	85.7	33.8	7.5	1,680	7,088
	Car	3.5	171.0	34.2	6.1	401	1,394
	Bus	5.9	100.6	42.2	8.4	568	3,360
	Walk	1.5	0.0	19.4	4.5	434	634
	Cycle	2.6	0.0	26.3	6.0	200	526
	Metro/rail	15.3	239.0	70.1	13.1	77	1,175
Business	All	13.5	327.7	47.1	17.2	239	3,222
	Car	10.2	478.0	40.6	15.0	133	1,352
	Bus	8.1	100.8	48.4	10.1	35	282
	Walk	1.6	0.0	21.5	4.6	29	47
	Cycle	3.0	0.0	28.4	6.3	8	25
	Metro/rail	44.9	328.5	97.5	27.6	34	1,516
Other	All	6.4	105.3	37.7	10.2	8,628	55,540
	Car	7.1	199.2	37.5	11.3	2,446	17,317
	Bus	7.1	100.7	45.3	9.4	2,233	15,834
	Walk	1.7	0.0	22.6	4.6	2,481	4,299
	Cycle	2.8	0.0	27.1	6.1	730	2,018
	Metro/rail	21.8	265.7	76.8	17.0	738	16,072
All	All	7.3	122.5	40.2	11.0	18,428	135,375
	Car	6.1	226.3	36.5	10.1	5,075	31,157
	Bus	7.7	100.8	47.1	9.8	4,940	38,060
	Walk	1.6	0.0	21.4	4.6	4,471	7,316
	Cycle	2.8	0.0	27.5	6.2	1,675	4,766
	Metro/rail	23.8	269.0	80.2	17.8	2,268	54,075

Table 5.1 and **Table 5.2** summarize modal split results by all purposes for the study area (within Beijing Sixth Ring Road). The comparison of the 2010 modelled travel patterns with the observed have been analysed in Chapter 4 above in model verification. The main purpose of the tables here is to present the model results in a way that can be readily compared with the model outputs for 2030. The model results by demand segment show that the socio-economic and income profiles play a significant role in influencing the average lengths of journeys (e.g. average commuting journey lengths are 10, 8.7 and 8.4km respectively for the high, medium and low income groups), and the car shares (since lower income groups have much lower car ownership). The average journey lengths and mode share patterns conform well to the observed, and thus form a reasonably good starting point for examining future year policy scenario tests.

5.2. Reference scenario 2030

As discussed in **Chapter 4**, the 2030 reference scenario is defined by **(1)** jobs and resident household locations as predicted in RSE-Beijing for the reference scenario; **(2)** the floating population is assumed to increase at the same rate as the resident households in each model zone; **(3)** the currently planned transport investments, especially the expressways, metro lines, rail projects etc. are incorporated into the multimodal transport networks for connectivity; **(4)** in Beijing, the congested road speeds as estimated for Feb 2008 and used in the 2010 model are assumed to remain the same, in line with the model test approach discussed above; **(5)** all transport costs are assumed to remain the same in real terms (i.e. the public transport fares increase at the same rate as inflation, and the fuel efficiency improvements of car engines are counter-balanced by consumer choice of larger and heavier vehicles such as SUVs); **(6)** the valuation of time goes up in line with income for each household group.

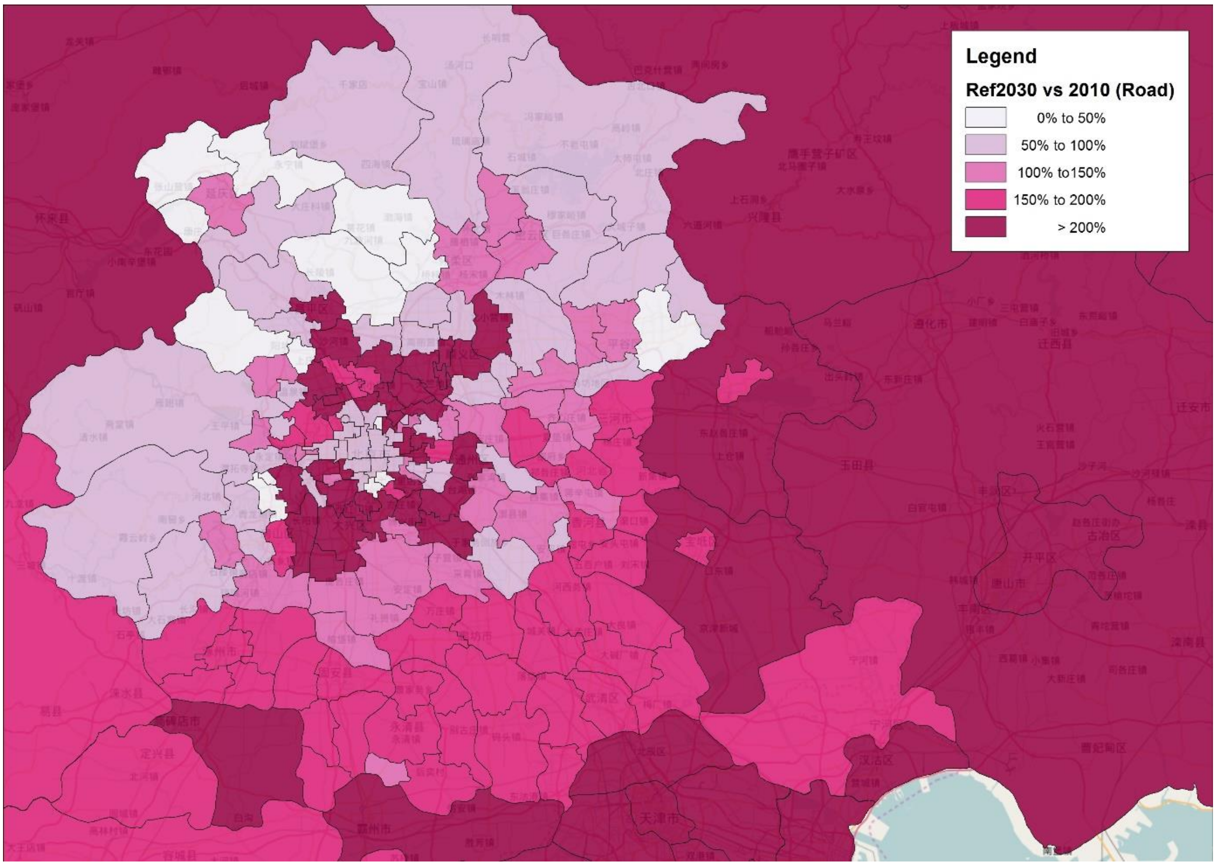


Figure 5.1. Road traffic comparison: 2030 reference case vs 2010

The road traffic comparison map above (**Figure 5.1**) shows that road traffic volume (measured in pcu's on road) surges in 2-4 times in the areas outside the main built up area of Beijing. Inside the Beijing main built up area, the increase is less scorching, ranging from 50%-100%. The rail traffic comparison map (**Figure 5.2**) shows that rail and metro trip volume grows significantly; especially in the suburban area surround Beijing, the growth is up to three times more or over.

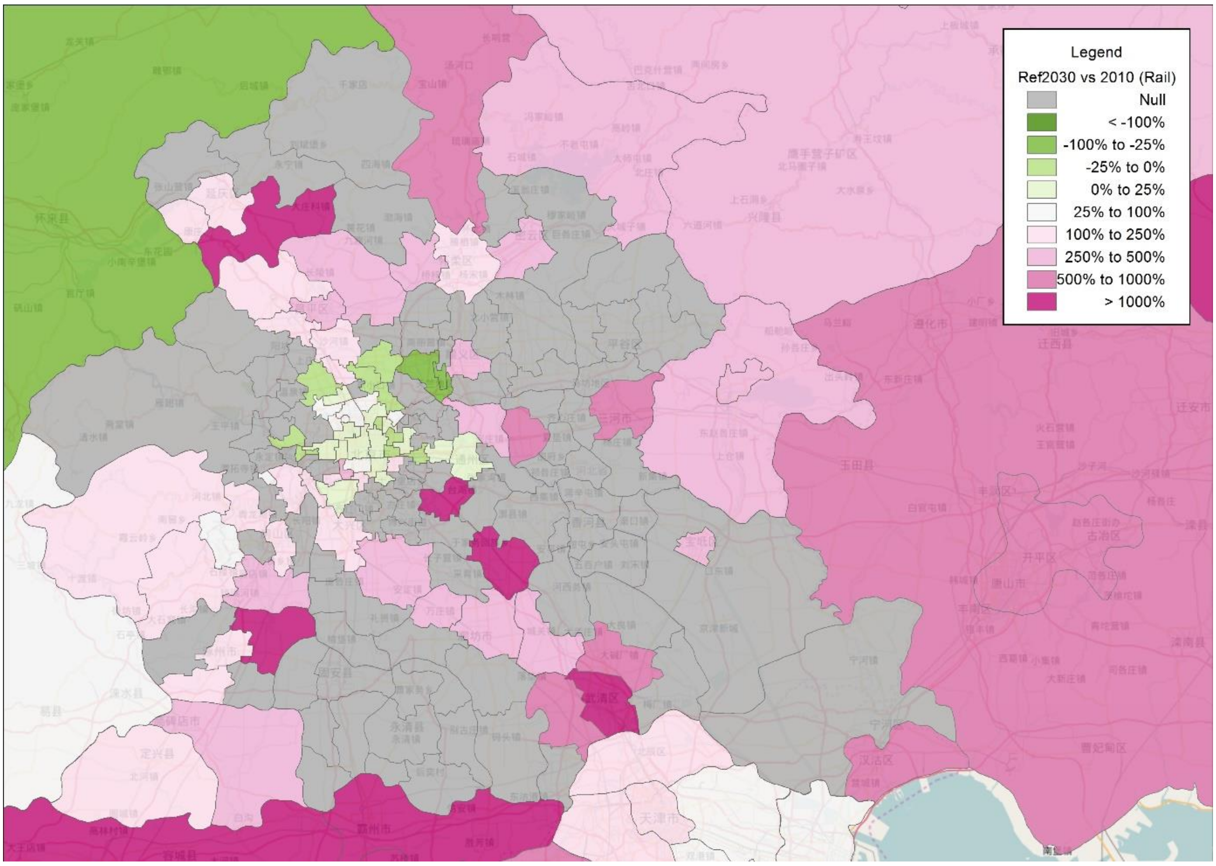


Figure 5.2. Rail traffic volume: 2030 reference case vs 2010

Table 5.3 and **Table 5.4** summarize the modal split results by all purposes for 2030 model. The 2030 reference case results confirm that if the road congestion conditions remain the same as in 2010, the morning peak passenger trip volume is likely to rise by 54.3%, and trip-km by 99.2%. Car traffic in particular will rise by 154.7% and car trip-km by 369.2%. In spite of the significant further expansion of the metro network, the rise in trip volume and trip-km are quite modest (38.3% and 30.9% respectively), and for commuting overall the metro passenger volume would only rise by 5.5% and trip-km 0.4%, as the more diffused jobs and residential locations coupled with a strong shift to higher income, car owning households make car travel a better choice in the newly expanded suburban areas. Buses on the whole have managed to hold on to its mode share, whilst walk and particularly cycling suffer an overall decline in mode share. This confirms our expectation that there is a very substantial surge in travel demand, and the foreseen transformations of the economy, demography and lifestyles are the dominant influences upon travel demand, and this non-marginal change will have profound impacts on the urban transport systems. In particular, the public transport modes can potentially be facing a serious challenge. Car travel demand will rise greatly for all income groups if the road speeds are kept at the 2010 network conditions.

Table 5.3. Summary by travel demand segment and mode: 2030 reference case vs 2010

Scenario tests								Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.1*	*405.8*	*44.2*	*15.0*	*1,992*	*22,008*	*11%*	*58%*	*-4%*	*15%*	*42%*	*57%*
	Car	12.6	601.3	43.0	17.6	1,126	14,159	48%	43%	10%	35%	105%	205%
	Bus	5.5	100.5	41.6	7.9	344	1,877	-19%	0%	-8%	-11%	12%	-9%
	Walk	1.4	0.0	18.2	4.5	168	228	-5%	-	-5%	-1%	3%	-2%
	Cycle	2.6	0.0	26.4	6.0	63	165	-9%	-	-5%	-4%	-4%	-13%
	Metro/rail	19.2	331.1	70.9	16.2	291	5,579	-11%	7%	-6%	-5%	-9%	-19%
2	*All*	*9.2*	*264.9*	*42.8*	*12.9*	*6,524*	*59,805*	*6%*	*99%*	*-4%*	*10%*	*43%*	*52%*
	Car	9.1	405.1	40.3	13.5	3,251	29,584	105%	95%	16%	77%	165%	445%
	Bus	6.0	100.6	42.4	8.4	1,439	8,570	-28%	0%	-13%	-17%	13%	-18%
	Walk	1.4	0.0	18.3	4.5	682	933	-9%	-	-7%	-1%	-17%	-24%
	Cycle	2.5	0.0	25.8	5.9	290	736	-11%	-	-6%	-5%	-26%	-34%
	Metro/rail	23.2	309.6	77.9	17.9	861	19,982	-7%	17%	-6%	0%	1%	-5%
3	*All*	*8.4*	*171.6*	*42.3*	*11.9*	*2,749*	*23,073*	*0%*	*109%*	*0%*	*1%*	*43%*	*43%*
	Car	6.3	261.0	37.4	10.1	1,143	7,195	99%	90%	16%	72%	256%	610%
	Bus	6.9	100.7	44.6	9.3	737	5,069	-40%	0%	-21%	-23%	39%	-16%
	Walk	1.4	0.0	18.7	4.5	368	515	-13%	-	-11%	-2%	-32%	-41%
	Cycle	2.6	0.0	26.2	6.0	155	405	-18%	-	-11%	-8%	-44%	-55%
	Metro/rail	28.6	286.5	85.8	20.0	346	9,890	-2%	18%	-1%	-1%	39%	35%
4	*All*	*6.5*	*224.3*	*38.8*	*10.1*	*331*	*2,160*	*32%*	*67%*	*7%*	*24%*	*43%*	*89%*
	Car	7.7	377.9	39.9	11.6	152	1,174	65%	56%	10%	50%	92%	217%
	Bus	5.3	100.5	40.5	7.9	94	498	-4%	0%	-1%	-2%	21%	16%
	Walk	1.3	0.0	18.0	4.4	43	58	-3%	-	-3%	0%	2%	-1%
	Cycle	2.4	0.0	25.1	5.7	16	38	-3%	-	-2%	-2%	-2%	-6%
	Metro/rail	15.0	285.4	69.3	12.9	26	392	3%	12%	0%	4%	54%	59%
5	*All*	*5.7*	*161.5*	*37.6*	*9.0*	*1,923*	*10,886*	*35%*	*92%*	*11%*	*21%*	*60%*	*115%*
	Car	6.0	274.5	38.1	9.4	779	4,651	82%	72%	12%	62%	171%	394%
	Bus	5.7	100.6	41.4	8.2	617	3,498	-3%	0%	-2%	-2%	47%	42%
	Walk	1.4	0.0	18.3	4.5	279	379	-6%	-	-5%	-1%	-7%	-13%
	Cycle	2.5	0.0	25.4	5.8	119	294	-5%	-	-3%	-2%	-15%	-19%
	Metro/rail	16.1	270.7	70.4	13.7	128	2,063	4%	15%	0%	4%	132%	142%
6	*All*	*5.0*	*113.6*	*36.4*	*8.3*	*351*	*1,763*	*39%*	*139%*	*18%*	*17%*	*43%*	*99%*
	Car	4.5	195.2	36.1	7.4	117	521	90%	84%	14%	67%	236%	539%
	Bus	6.3	100.6	43.0	8.8	129	809	-6%	0%	-3%	-3%	85%	74%
	Walk	1.4	0.0	18.7	4.5	63	88	-9%	-	-8%	-1%	-32%	-38%
	Cycle	2.6	0.0	25.9	5.9	27	68	-7%	-	-4%	-3%	-40%	-44%
	Metro/rail	16.7	254.9	72.8	13.8	17	276	-1%	17%	1%	-3%	269%	264%
7	*All*	*34.0*	*1335.2*	*58.8*	*34.6*	*54*	*1,817*	*0%*	*132%*	*-10%*	*10%*	*40%*	*40%*
	Car	42.7	1749.9	63.9	40.1	37	1,593	127%	108%	36%	67%	66%	277%
	Bus	5.5	100.6	42.5	7.8	5	28	-10%	0%	-3%	-7%	16%	4%
	Walk	1.6	0.0	20.8	4.5	4	7	-2%	-	-2%	0%	14%	11%
	Cycle	3.1	0.0	29.1	6.4	1	3	-3%	-	-2%	-1%	11%	7%
	Metro/rail	32.4	976.2	74.6	26.1	6	185	-75%	149%	-57%	-42%	-13%	-78%
8	*All*	*16.2*	*643.6*	*47.3*	*20.5*	*224*	*3,614*	*59%*	*107%*	*7%*	*48%*	*44%*	*129%*
	Car	18.1	816.0	47.1	23.0	163	2,951	97%	86%	18%	68%	84%	263%
	Bus	6.2	100.6	43.8	8.4	19	118	-23%	0%	-9%	-15%	-11%	-31%
	Walk	1.6	0.0	20.6	4.5	15	24	-4%	-	-4%	-1%	-14%	-17%
	Cycle	2.8	0.0	27.1	6.1	4	12	-7%	-	-4%	-3%	-18%	-23%
	Metro/rail	23.6	402.8	74.7	18.9	22	510	-7%	26%	-6%	-1%	-1%	-7%
9	*All*	*12.5*	*466.4*	*44.8*	*16.7*	*65*	*812*	*64%*	*164%*	*7%*	*53%*	*44%*	*136%*
	Car	13.4	589.8	43.9	18.3	47	629	149%	128%	21%	105%	118%	443%
	Bus	7.0	100.7	45.3	9.3	6	45	-27%	0%	-12%	-16%	-27%	-46%
	Walk	1.6	0.0	20.6	4.5	5	7	-7%	-	-6%	-1%	-36%	-41%
	Cycle	2.7	0.0	26.8	6.0	1	3	-10%	-	-6%	-4%	-42%	-48%
	Metro/rail	22.7	343.1	76.1	17.9	6	128	-1%	20%	-4%	3%	3%	1%
10	*All*	*10.9*	*287.9*	*43.2*	*15.2*	*2,026*	*22,155*	*42%*	*73%*	*7%*	*33%*	*42%*	*102%*
	Car	15.1	504.5	44.3	20.4	882	13,324	68%	61%	13%	50%	94%	226%
	Bus	5.8	100.6	42.0	8.2	500	2,884	-6%	0%	-2%	-4%	24%	16%
	Walk	1.6	0.0	21.1	4.6	307	493	-3%	-	-2%	0%	2%	-1%
	Cycle	2.6	0.0	26.2	5.9	80	206	-4%	-	-2%	-2%	-1%	-5%
	Metro/rail	20.4	341.6	73.0	16.7	258	5,247	1%	17%	-2%	3%	42%	44%
11	*All*	*10.3*	*207.8*	*42.2*	*14.6*	*10,042*	*103,401*	*58%*	*103%*	*11%*	*42%*	*76%*	*179%*
	Car	13.9	349.6	43.4	19.2	4,319	60,123	100%	88%	16%	72%	166%	432%
	Bus	6.2	100.6	42.9	8.6	2,575	15,886	-12%	0%	-5%	-7%	69%	49%
	Walk	1.6	0.0	21.6	4.6	1,647	2,714	-4%	-	-4%	-1%	4%	0%
	Cycle	2.6	0.0	26.1	5.9	472	1,219	-6%	-	-3%	-3%	-1%	-7%
	Metro/rail	22.8	309.0	76.0	18.0	1,029	23,458	2%	19%	-2%	4%	108%	112%
12	*All*	*8.4*	*141.6*	*39.8*	*12.6*	*2,159*	*18,115*	*67%*	*144%*	*16%*	*45%*	*44%*	*140%*
	Car	11.3	230.9	41.4	16.4	907	10,270	115%	99%	16%	84%	149%	435%
	Bus	6.7	100.7	44.1	9.1	561	3,766	-23%	0%	-11%	-14%	83%	41%
	Walk	1.7	0.0	22.2	4.6	430	734	-6%	-	-5%	-1%	-28%	-32%
	Cycle	2.6	0.0	26.3	6.0	114	299	-8%	-	-5%	-4%	-34%	-40%
	Metro/rail	20.7	269.7	75.7	16.4	147	3,046	-6%	18%	-3%	-3%	137%	124%

Table 5.4. Summary by trip purpose and mode: 2030 reference case vs 2010

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	***All***	***9.3***	***267.0***	***42.9***	***13.0***	***11,264***	***104,886***	***6%***	***87%***	***-3%***	***9%***	***43%***	***51%***
	Car	9.2	415.3	40.3	13.8	5,520	50,938	74%	64%	13%	54%	163%	359%
	Bus	6.2	100.6	42.9	8.6	2,520	15,515	-30%	0%	-15%	-18%	20%	-17%
	Walk	1.4	0.0	18.4	4.5	1,218	1,676	-10%	-	-9%	-2%	-20%	-28%
	Cycle	2.6	0.0	26.0	5.9	508	1,305	-14%	-	-8%	-6%	-31%	-41%
	Metro/rail	23.7	308.4	78.4	18.1	1,498	35,452	-5%	14%	-5%	0%	6%	0%
School	***All***	***5.7***	***163.0***	***37.6***	***9.1***	***2,605***	***14,808***	***35%***	***90%***	***11%***	***21%***	***55%***	***109%***
	Car	6.1	280.6	38.1	9.5	1,047	6,346	74%	64%	11%	56%	161%	355%
	Bus	5.7	100.6	41.5	8.3	840	4,806	-3%	0%	-2%	-2%	48%	43%
	Walk	1.4	0.0	18.3	4.5	385	525	-7%	-	-6%	-1%	-11%	-17%
	Cycle	2.5	0.0	25.5	5.8	162	401	-6%	-	-3%	-3%	-19%	-24%
	Metro/rail	16.0	271.4	70.5	13.6	171	2,731	5%	14%	1%	4%	122%	133%
Business	***All***	***18.2***	***718.1***	***48.6***	***22.5***	***342***	***6,243***	***35%***	***119%***	***3%***	***31%***	***43%***	***94%***
	Car	20.9	913.8	49.0	25.6	248	5,173	105%	91%	21%	70%	86%	283%
	Bus	6.2	100.6	43.9	8.5	31	191	-23%	0%	-9%	-16%	-12%	-32%
	Walk	1.6	0.0	20.6	4.5	24	38	-5%	-	-4%	-1%	-16%	-20%
	Cycle	2.8	0.0	27.4	6.1	7	19	-6%	-	-4%	-3%	-20%	-25%
	Metro/rail	25.0	491.9	74.9	20.0	33	823	-44%	50%	-23%	-28%	-2%	-46%
Other	***All***	***10.1***	***209.2***	***42.0***	***14.4***	***14,228***	***143,670***	***57%***	***99%***	***11%***	***41%***	***65%***	***159%***
	Car	13.7	354.3	43.2	19.0	6,109	83,718	94%	78%	15%	68%	150%	383%
	Bus	6.2	100.6	42.9	8.7	3,635	22,536	-13%	0%	-5%	-8%	63%	42%
	Walk	1.7	0.0	21.7	4.6	2,385	3,941	-5%	-	-4%	-1%	-4%	-8%
	Cycle	2.6	0.0	26.1	6.0	665	1,724	-6%	-	-4%	-3%	-9%	-15%
	Metro/rail	22.1	310.8	75.4	17.6	1,434	31,752	2%	17%	-2%	4%	94%	98%
All	***All***	***9.5***	***234.0***	***42.0***	***13.5***	***28,439***	***269,607***	***29%***	***91%***	***4%***	***24%***	***54%***	***99%***
	Car	11.3	385.1	41.7	16.3	12,924	146,173	84%	70%	14%	61%	155%	369%
	Bus	6.1	100.6	42.8	8.6	7,026	43,048	-20%	0%	-9%	-12%	42%	13%
	Walk	1.5	0.0	20.3	4.5	4,012	6,180	-6%	-	-5%	-1%	-10%	-16%
	Cycle	2.6	0.0	26.0	5.9	1,342	3,449	-10%	-	-6%	-4%	-20%	-28%
	Metro/rail	22.6	309.4	76.5	17.7	3,136	70,758	-5%	15%	-5%	-1%	38%	31%

5.3. Short term impacts of strategic transport interventions

5.3.1. Overview

Six strategic transport interventions that cover the key ideas such as put forward in BTRC (2012) have been tested in as generic as possible implementations for generalizable insights. The tests are:

(1) **S01** – road pricing for cars: a road toll of 0.2 yuan/km in 2010 prices is applied on all roads; this is in line with the current, active interest in introducing road charging in the Greater Beijing area, particularly in Beijing;

(2) **S02** – Free bus transport: bus services are offered free of charge across the Greater Beijing area; this is to test initiative to make buses free in order to attract ridership;

(3) **S03** – Higher metro charges: in addition to the flat fare of 2 yuan per ride, a 0.5 yuan/km distance based fare is introduced; this is test the claim that the metro fares are too low, and in fact since we have introduced this test for the dissertation work, the metro fares in Beijing have been raised to about 75% of the tested level;

(4) **S04** – Car origin and destination access/parking times are increased by 10 minutes at each end for the central Beijing four districts to simulate tighter car access and parking controls in the very dense urban areas;

(5) **S05** – Bus origin and destination access and egress times are reduced by 7.5 minutes at each end for the urban and suburban zones in Beijing and Tianjin and in Hebei (for the rural and far suburb zones the reduction is 10 minutes, and for intrazonal trips, 5 minutes); this is to simulate the introduction of BRT systems with more efficient access/egress and boarding/alighting as well as more optimised headways;

(6) **S06** – Building on S05, the origin and destination access/egress times are reduced for all zones served by metro and light rail by 7.5 minutes (5 minutes for intrazonal trip); this is to simulate improved access/egress and better integration with land use in and around the stations/stops.

Table 5.5. Summary by mode: Scenario S01 – S06 vs Reference Case

Scenario tests								Percentage changes from reference case					
Scenario	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
S01	***All***	***9***	***262***	***44***	***13***	***28,439***	***269,195***	***0%***	***12%***	***4%***	***-4%***	***0%***	***0%***
	Car	9	521	40	14	9,860	92,682	-17%	35%	-5%	-13%	-24%	-37%
	Bus	7	101	44	9	8,242	55,144	9%	0%	3%	6%	17%	28%
	Walk	2	0	21	5	4,414	6,882	1%	-	1%	0%	10%	11%
	Cycle	3	0	26	6	1,508	3,963	2%	-	1%	1%	12%	15%
	Metro/rail	25	335	81	19	4,415	110,523	11%	8%	6%	5%	41%	56%
S02	***All***	***10***	***197***	***43***	***14***	***28,439***	***272,738***	***1%***	***-16%***	***1%***	***0%***	***0%***	***1%***
	Car	12	405	42	17	11,550	138,055	6%	5%	1%	5%	-11%	-6%
	Bus	6	0	43	9	9,156	55,241	-2%	-100%	-1%	-1%	30%	28%
	Walk	2	0	20	5	3,505	5,344	-1%	-	-1%	0%	-13%	-14%
	Cycle	3	0	26	6	1,159	2,972	0%	-	0%	0%	-14%	-14%
	Metro/rail	23	307	77	18	3,070	71,127	3%	-1%	0%	3%	-2%	1%
S03	***All***	***9***	***287***	***40***	***14***	***28,439***	***268,038***	***-1%***	***22%***	***-5%***	***4%***	***0%***	***-1%***
	Car	13	449	43	18	14,667	192,950	16%	17%	3%	13%	13%	32%
	Bus	7	101	45	9	7,399	50,440	11%	0%	4%	7%	5%	17%
	Walk	2	0	20	5	4,082	6,320	1%	-	0%	0%	2%	2%
	Cycle	3	0	26	6	1,377	3,609	2%	-	1%	1%	3%	5%
	Metro/rail	16	902	64	15	914	14,719	-29%	192%	-17%	-14%	-71%	-79%
S04	***All***	***9***	***228***	***43***	***13***	***28,439***	***269,615***	***0%***	***-3%***	***1%***	***-1%***	***0%***	***0%***
	Car	12	393	43	16	11,923	138,869	3%	2%	3%	0%	-8%	-5%
	Bus	6	101	43	9	7,478	45,415	-1%	0%	0%	-1%	6%	5%
	Walk	2	0	20	5	4,228	6,544	0%	-	0%	0%	5%	6%
	Cycle	3	0	26	6	1,427	3,685	0%	-	0%	0%	6%	7%
	Metro/rail	22	308	76	18	3,383	75,101	-2%	0%	-1%	-1%	8%	6%
S05	***All***	***10***	***221***	***39***	***15***	***28,439***	***275,692***	***2%***	***-6%***	***-8%***	***11%***	***0%***	***2%***
	Car	14	455	43	19	8,954	122,723	21%	18%	3%	18%	-31%	-16%
	Bus	6	101	33	11	13,444	82,944	1%	0%	-24%	32%	91%	93%
	Walk	1	0	20	5	2,552	3,804	-3%	-	-3%	0%	-36%	-38%
	Cycle	3	0	26	6	828	2,120	0%	-	0%	0%	-38%	-39%
	Metro/rail	24	318	78	19	2,661	64,101	7%	3%	2%	5%	-15%	-9%
S06	***All***	***10***	***209***	***39***	***15***	***28,439***	***277,534***	***3%***	***-11%***	***-8%***	***12%***	***0%***	***3%***
	Car	13	428	42	18	7,954	102,878	14%	11%	2%	12%	-38%	-30%
	Bus	6	101	32	11	12,823	76,901	-2%	0%	-25%	30%	83%	79%
	Walk	1	0	20	5	2,483	3,663	-4%	-	-4%	-1%	-38%	-41%
	Cycle	2	0	26	6	795	1,984	-3%	-	-2%	-1%	-41%	-42%
	Metro/rail	21	284	64	20	4,385	92,108	-7%	-8%	-16%	11%	40%	30%

Table 5.5 represents the overall results of the strategic transport intervention scenario in Test 1-6 for short-term effects, where the total flows are fixed on each OD zone pair and the model inputs cause the mode shares on each OD pair to change.

In subsections below, we summarise the results by presenting the same summary data tables and road and rail traffic maps in order to understand both the impacts on the transport modes and geographic areas. The more detailed results (e.g. by travel demand segment and by mode) can be found in **Appendix 5**.

5.3.2. Test 1 – S01

Table 5.6 present the comparison of modal split result between S01 and the Reference Case. As expected **S01** does not alter the overall trip volume and only reduces the total trip-km marginally. However, there is a significant reduction in car trip volume (by 24%) and car trip-km (by 37%). The impacts are felt most by the low-income groups (**Appendix 5 - Table A5.1**). All non-car modes gain mode share. However, it is the metro services that gain the most, increasing the trip volume by 41% and trip-km by 56% when compared with 2030 reference case.

Table 5.6. Summary by trip purpose and mode: S01 vs Reference Case

Scenario tests								Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	***All***	***9.3***	***278.2***	***44.2***	***12.6***	***11,264***	***104,729***	***0%***	***4%***	***3%***	***-3%***	***0%***	***0%***
	Car	7.7	507.5	38.5	12.0	4,318	33,236	-17%	22%	-4%	-13%	-22%	-35%
	Bus	6.5	100.7	44.0	8.9	3,023	19,785	6%	0%	2%	4%	20%	28%
	Walk	1.4	0.0	18.7	4.5	1,367	1,913	2%	-	1%	0%	12%	14%
	Cycle	2.6	0.0	26.3	6.0	585	1,538	2%	-	1%	1%	15%	18%
	Metro/rail	24.5	323.7	80.1	18.4	1,971	48,257	3%	5%	2%	1%	32%	36%
School	***All***	***5.6***	***173.4***	***37.9***	***8.9***	***2,605***	***14,700***	***-1%***	***6%***	***1%***	***-1%***	***0%***	***-1%***
	Car	5.2	351.7	36.9	8.5	840	4,403	-13%	25%	-3%	-10%	-20%	-31%
	Bus	5.8	100.6	41.9	8.4	954	5,577	2%	0%	1%	1%	14%	16%
	Walk	1.4	0.0	18.5	4.5	420	579	1%	-	1%	0%	9%	10%
	Cycle	2.5	0.0	25.7	5.9	180	450	1%	-	1%	1%	11%	12%
	Metro/rail	17.4	284.6	72.5	14.4	212	3,691	9%	5%	3%	6%	24%	35%
Business	***All***	***18.3***	***924.9***	***49.6***	***22.1***	***342***	***6,247***	***0%***	***29%***	***2%***	***-2%***	***0%***	***0%***
	Car	18.8	1205.9	47.3	23.8	228	4,281	-10%	32%	-3%	-7%	-8%	-17%
	Bus	7.2	100.7	46.1	9.4	36	257	16%	0%	5%	10%	16%	35%
	Walk	1.6	0.0	20.8	4.5	26	41	1%	-	1%	0%	8%	9%
	Cycle	2.9	0.0	27.7	6.2	7	21	2%	-	1%	1%	9%	11%
	Metro/rail	36.4	838.1	84.0	26.0	45	1,648	46%	70%	12%	30%	37%	100%
Other	***All***	***10.1***	***248.7***	***44.2***	***13.7***	***14,228***	***143,518***	***0%***	***19%***	***5%***	***-5%***	***0%***	***0%***
	Car	11.3	530.1	40.9	16.6	4,473	50,763	-17%	50%	-5%	-13%	-27%	-39%
	Bus	7.0	100.7	44.7	9.4	4,230	29,526	13%	0%	4%	8%	16%	31%
	Walk	1.7	0.0	21.9	4.6	2,601	4,348	1%	-	1%	0%	9%	10%
	Cycle	2.7	0.0	26.5	6.0	737	1,954	2%	-	1%	1%	11%	13%
	Metro/rail	26.0	339.3	82.2	19.0	2,187	56,927	18%	9%	9%	8%	52%	79%
All	***All***	***9.5***	***261.6***	***43.7***	***13.0***	***28,439***	***269,195***	***0%***	***12%***	***4%***	***-4%***	***0%***	***0%***
	Car	9.4	520.6	39.7	14.2	9,860	92,682	-17%	35%	-5%	-13%	-24%	-37%
	Bus	6.7	100.7	44.1	9.1	8,242	55,144	9%	0%	3%	6%	17%	28%
	Walk	1.6	0.0	20.6	4.5	4,414	6,882	1%	-	1%	0%	10%	11%
	Cycle	2.6	0.0	26.3	6.0	1,508	3,963	2%	-	1%	1%	12%	15%
	Metro/rail	25.0	334.8	80.8	18.6	4,415	110,523	11%	8%	6%	5%	41%	56%

The road traffic comparison map below (**Figure 5.3**) shows that road traffic volume (measured in pcu's on road) reduces by 30-40% in the areas outside the main built up area of Beijing. Inside the Beijing main built up area, the reduction is somewhat lower, ranging from 10-30%. The rail traffic comparison map (**Figure 5.4**) shows that rail and metro gain significantly as a fast mode of travel during the morning peak, with traffic rising by 50-75% in the main built up area of Beijing and up to 500% (from low initial levels) outside Beijing.

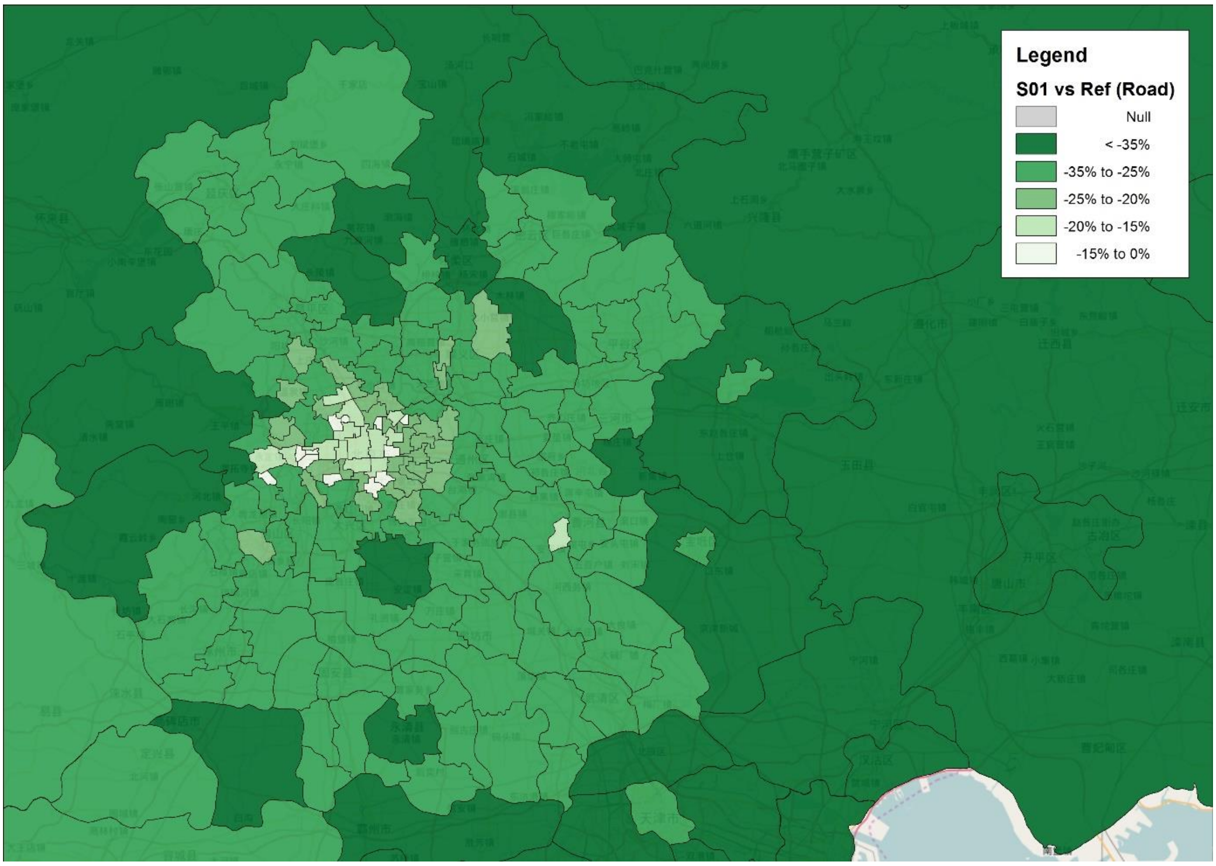


Figure 5.3. Changes of road traffic volume: S01 vs Reference Case

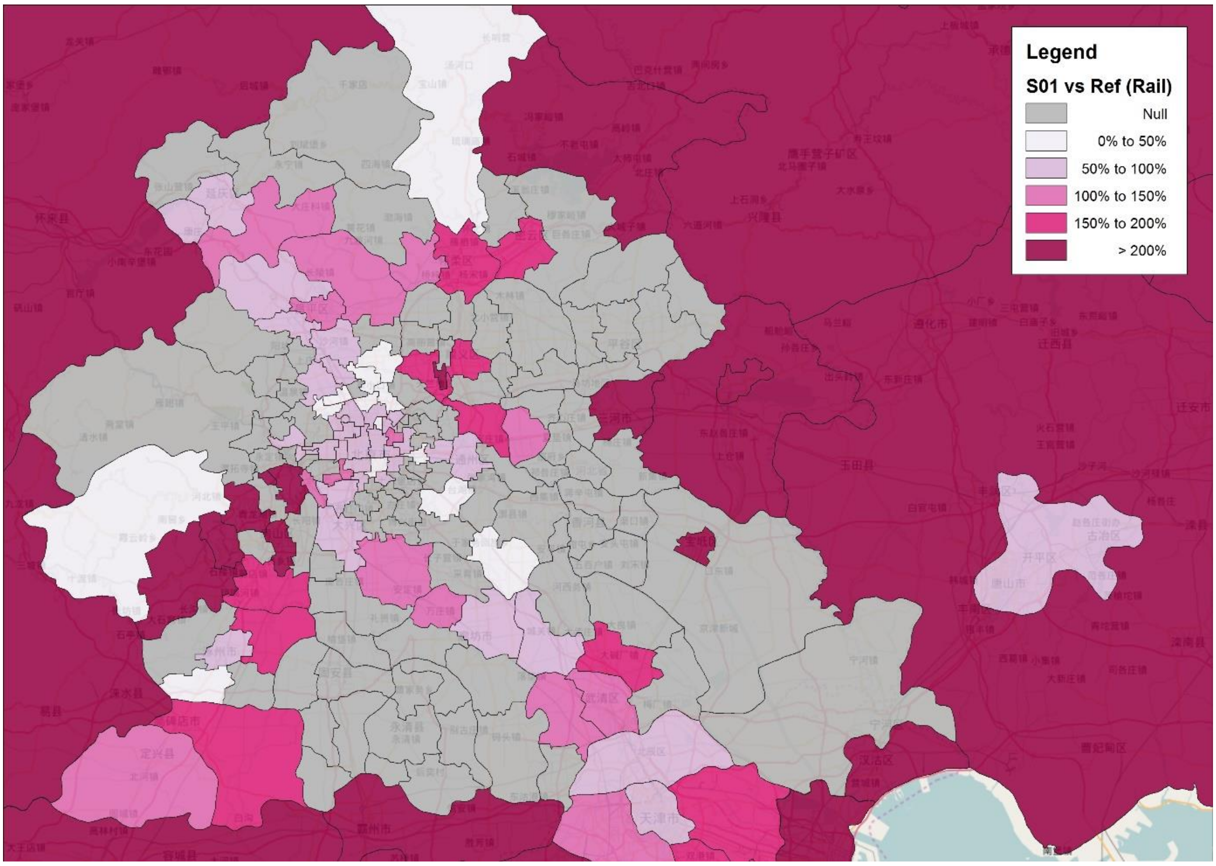


Figure 5.4. Changes of railway traffic volume: S01 vs Reference Case

5.3.3. Test 2 – S02

Although **S02** is an eye-catching initiative, its effects appear to be quite limited. Overall, it does not alter the total trip volume and, because of a reduction in travel costs, it raises the total trip-km slightly. However, there is only a surge in bus share, such as an increase in overall trip volume (by 30%) and trip-km (by 28%) (**Table 5.7**). Employers' business trips are less affected. In contrast, the impacts are felt most by the low-income groups (**Appendix 5 - Table A5.2**). All non-bus modes lose mode share as a result, including walking and cycling. Its impact on reducing car trip appears to be very small.

Table 5.7. Summary by trip purpose and mode: S02 vs Reference Case

Scenario tests								Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	*All*	*9.4*	*229.2*	*43.4*	*13.0*	*11,264*	*106,148*	*1%*	*-14%*	*1%*	*0%*	*0%*	*1%*
	Car	9.7	434.7	40.5	14.4	4,906	47,515	5%	5%	1%	4%	-11%	-7%
	Bus	6.1	0.0	42.6	8.5	3,384	20,477	-2%	-100%	-1%	-1%	34%	32%
	Walk	1.4	0.0	18.3	4.5	1,065	1,453	-1%	-	-1%	0%	-13%	-13%
	Cycle	2.6	0.0	26.0	5.9	438	1,123	0%	-	0%	0%	-14%	-14%
	Metro/rail	24.2	305.0	78.3	18.5	1,471	35,580	2%	-1%	0%	2%	-2%	0%
School	*All*	*5.8*	*116.9*	*38.2*	*9.1*	*2,605*	*15,127*	*2%*	*-28%*	*1%*	*1%*	*0%*	*2%*
	Car	6.3	289.0	38.1	9.9	903	5,662	3%	3%	0%	3%	-14%	-11%
	Bus	5.6	0.0	41.3	8.2	1,068	6,005	-2%	-100%	-1%	-1%	27%	25%
	Walk	1.3	0.0	18.1	4.5	335	451	-1%	-	-1%	0%	-13%	-14%
	Cycle	2.5	0.0	25.4	5.8	138	340	-1%	-	0%	0%	-15%	-15%
	Metro/rail	16.7	272.1	70.5	14.2	160	2,669	4%	0%	0%	4%	-6%	-2%
Business	*All*	*18.3*	*702.7*	*48.7*	*22.5*	*342*	*6,247*	*0%*	*-2%*	*0%*	*0%*	*0%*	*0%*
	Car	21.1	922.8	49.1	25.8	243	5,135	1%	1%	0%	1%	-2%	-1%
	Bus	6.2	0.0	43.7	8.5	36	219	-1%	-100%	-1%	0%	16%	15%
	Walk	1.6	0.0	20.6	4.5	24	37	0%	-	0%	0%	-2%	-2%
	Cycle	2.8	0.0	27.4	6.1	7	18	0%	-	0%	0%	-2%	-2%
	Metro/rail	25.2	478.1	75.0	20.2	33	837	1%	-3%	0%	1%	1%	2%
Other	*All*	*10.2*	*174.9*	*42.5*	*14.4*	*14,228*	*145,217*	*1%*	*-16%*	*1%*	*0%*	*0%*	*1%*
	Car	14.5	373.9	43.6	20.0	5,497	79,743	6%	6%	1%	5%	-10%	-5%
	Bus	6.1	0.0	42.7	8.6	4,668	28,540	-1%	-100%	-1%	-1%	28%	27%
	Walk	1.6	0.0	21.5	4.6	2,081	3,403	-1%	-	-1%	0%	-13%	-14%
	Cycle	2.6	0.0	26.1	5.9	576	1,490	0%	-	0%	0%	-13%	-14%
	Metro/rail	22.8	308.3	75.5	18.1	1,405	32,041	3%	-1%	0%	3%	-2%	1%
All	*All*	*9.6*	*197.4*	*42.5*	*13.5*	*28,439*	*272,738*	*1%*	*-16%*	*1%*	*0%*	*0%*	*1%*
	Car	12.0	404.7	41.9	17.1	11,550	138,055	6%	5%	1%	5%	-11%	-6%
	Bus	6.0	0.0	42.5	8.5	9,156	55,241	-2%	-100%	-1%	-1%	30%	28%
	Walk	1.5	0.0	20.2	4.5	3,505	5,344	-1%	-	-1%	0%	-13%	-14%
	Cycle	2.6	0.0	26.0	5.9	1,159	2,972	0%	-	0%	0%	-14%	-14%
	Metro/rail	23.2	306.7	76.6	18.2	3,070	71,127	3%	-1%	0%	3%	-2%	1%

The road traffic comparison map below (**Figure 5.5**) does show that road traffic volume reduces by 10-20% across the study area, with the near suburbs of Beijing (where car ownership is the highest) reducing between 5-10%. The rail traffic comparison map (**Figure 5.6**) shows that the impacts on rail and metro are small, mostly reductions less than 5% in the main built up area of Beijing and up to 25% increases (from low initial levels) outside Beijing due to cheaper bus feeders to the regional rail services.

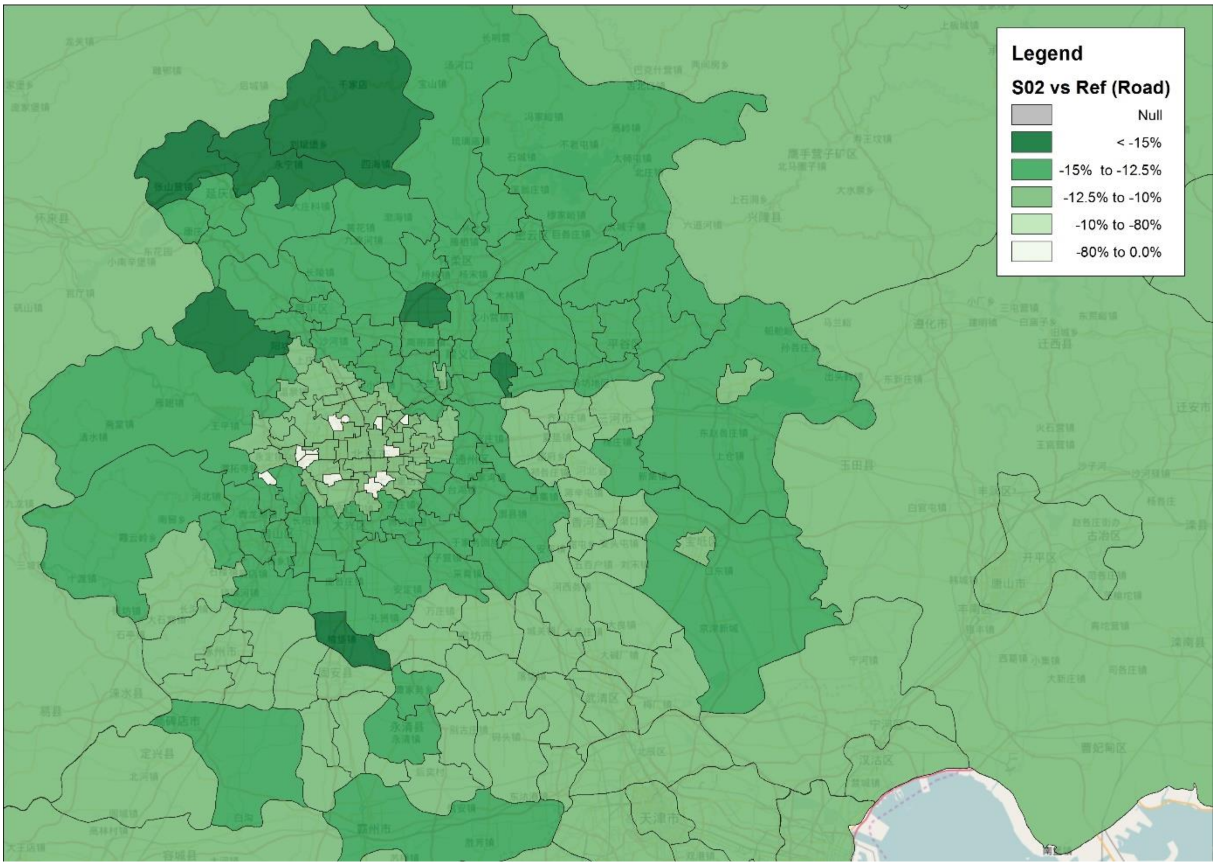


Figure 5.5. Road traffic comparison: S02 vs Reference Case

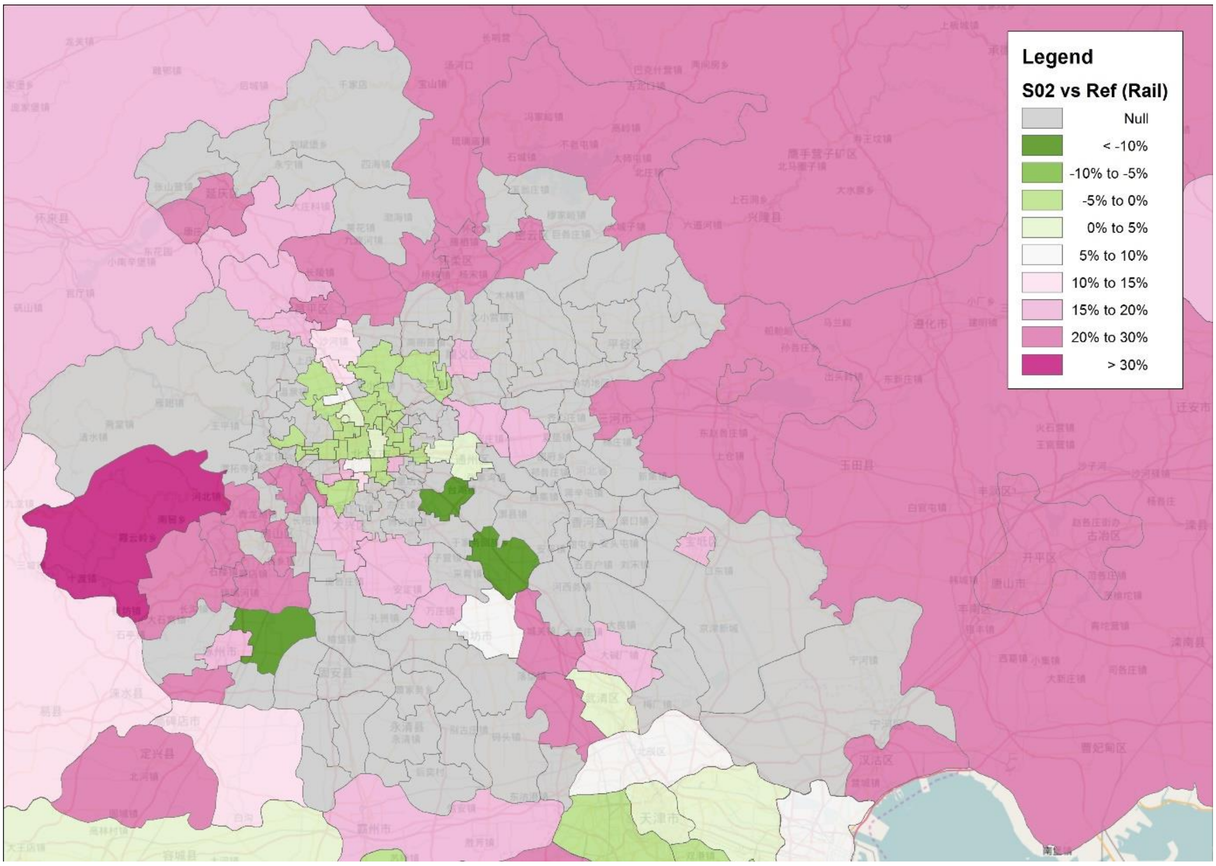


Figure 5.6. Rail traffic comparison: S02 vs Reference Case

5.3.4. Test 3 – S03

An increase in rail and metro fares under **S03** does not alter the overall trip volume and only reduces the total trip-km marginally. However, there is a significant reduction in rail and metro trip volume (by 71%) and trip-km (by 79%) as shown in **Table 5.8**. The impacts are felt most by the low-income groups (**Appendix 5 - Table A5.3**). All non-rail/metro modes gain mode share. However, it is the car that gains the most, increasing the trip volume by 13% and trip-km by 32% when compared with 2030 reference case, picking up many of the longer journeys by rail/metro.

Table 5.8. Summary by trip purpose and mode: S03 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	***All***	***9.3***	***346.8***	***40.8***	***13.7***	***11,264***	***104,588***	***0%***	***30%***	***-5%***	***5%***	***0%***	***0%***
	Car	11.5	508.8	42.0	16.4	6,342	72,802	24%	23%	4%	19%	15%	43%
	Bus	7.7	100.8	46.9	9.9	2,734	21,157	26%	0%	9%	15%	8%	36%
	Walk	1.4	0.0	18.5	4.5	1,238	1,717	1%	-	1%	0%	2%	2%
	Cycle	2.6	0.0	26.3	6.0	522	1,373	2%	-	1%	1%	3%	5%
	Metro/rail	17.6	944.2	65.3	16.2	428	7,539	-26%	206%	-17%	-11%	-71%	-79%
School	***All***	***5.6***	***186.3***	***36.4***	***9.2***	***2,605***	***14,563***	***-2%***	***14%***	***-3%***	***2%***	***0%***	***-2%***
	Car	7.0	316.9	38.7	10.8	1,124	7,812	15%	13%	2%	13%	7%	23%
	Bus	5.9	100.6	42.0	8.4	868	5,126	3%	0%	1%	2%	3%	7%
	Walk	1.4	0.0	18.4	4.5	392	537	0%	-	0%	0%	2%	2%
	Cycle	2.5	0.0	25.6	5.9	166	415	1%	-	1%	1%	2%	4%
	Metro/rail	12.3	762.7	61.7	11.9	55	674	-23%	181%	-12%	-13%	-68%	-75%
Business	***All***	***18.2***	***786.7***	***47.4***	***23.0***	***342***	***6,223***	***0%***	***10%***	***-3%***	***2%***	***0%***	***0%***
	Car	21.2	932.4	49.2	25.9	261	5,541	2%	2%	0%	1%	5%	7%
	Bus	6.4	100.6	44.5	8.6	31	201	3%	0%	1%	2%	3%	6%
	Walk	1.6	0.0	20.7	4.5	24	38	1%	-	0%	0%	1%	2%
	Cycle	2.8	0.0	27.7	6.2	7	19	2%	-	1%	1%	2%	4%
	Metro/rail	22.6	1218.3	67.9	20.0	19	423	-9%	148%	-9%	0%	-43%	-49%
Other	***All***	***10.0***	***245.3***	***39.9***	***15.1***	***14,228***	***142,663***	***-1%***	***17%***	***-5%***	***4%***	***0%***	***-1%***
	Car	15.4	396.9	44.4	20.8	6,941	106,795	12%	12%	3%	9%	14%	28%
	Bus	6.4	100.6	43.4	8.8	3,765	23,955	3%	0%	1%	1%	4%	6%
	Walk	1.7	0.0	21.7	4.6	2,427	4,028	0%	-	0%	0%	2%	2%
	Cycle	2.6	0.0	26.4	6.0	683	1,801	2%	-	1%	1%	3%	4%
	Metro/rail	14.7	862.7	62.3	14.2	413	6,084	-33%	178%	-17%	-19%	-71%	-81%
All	***All***	***9.4***	***286.6***	***40.0***	***14.1***	***28,439***	***268,038***	***-1%***	***22%***	***-5%***	***4%***	***0%***	***-1%***
	Car	13.2	448.7	43.0	18.4	14,667	192,950	16%	17%	3%	13%	13%	32%
	Bus	6.8	100.7	44.6	9.2	7,399	50,440	11%	0%	4%	7%	5%	17%
	Walk	1.5	0.0	20.4	4.5	4,082	6,320	1%	-	0%	0%	2%	2%
	Cycle	2.6	0.0	26.3	6.0	1,377	3,609	2%	-	1%	1%	3%	5%
	Metro/rail	16.1	902.1	63.8	15.1	914	14,719	-29%	192%	-17%	-14%	-71%	-79%

The road traffic comparison map below (**Figure 5.7**) shows that, reassuringly, there is very little impact on the road traffic volumes (mostly increases less than 5%). The rail traffic comparison map (**Figure 5.8**) shows that metro loses significantly by 50-100% in the main built up area of Beijing. In the wider region, rail and high speed rail picks up some of the long trips possibly involving re-routing.

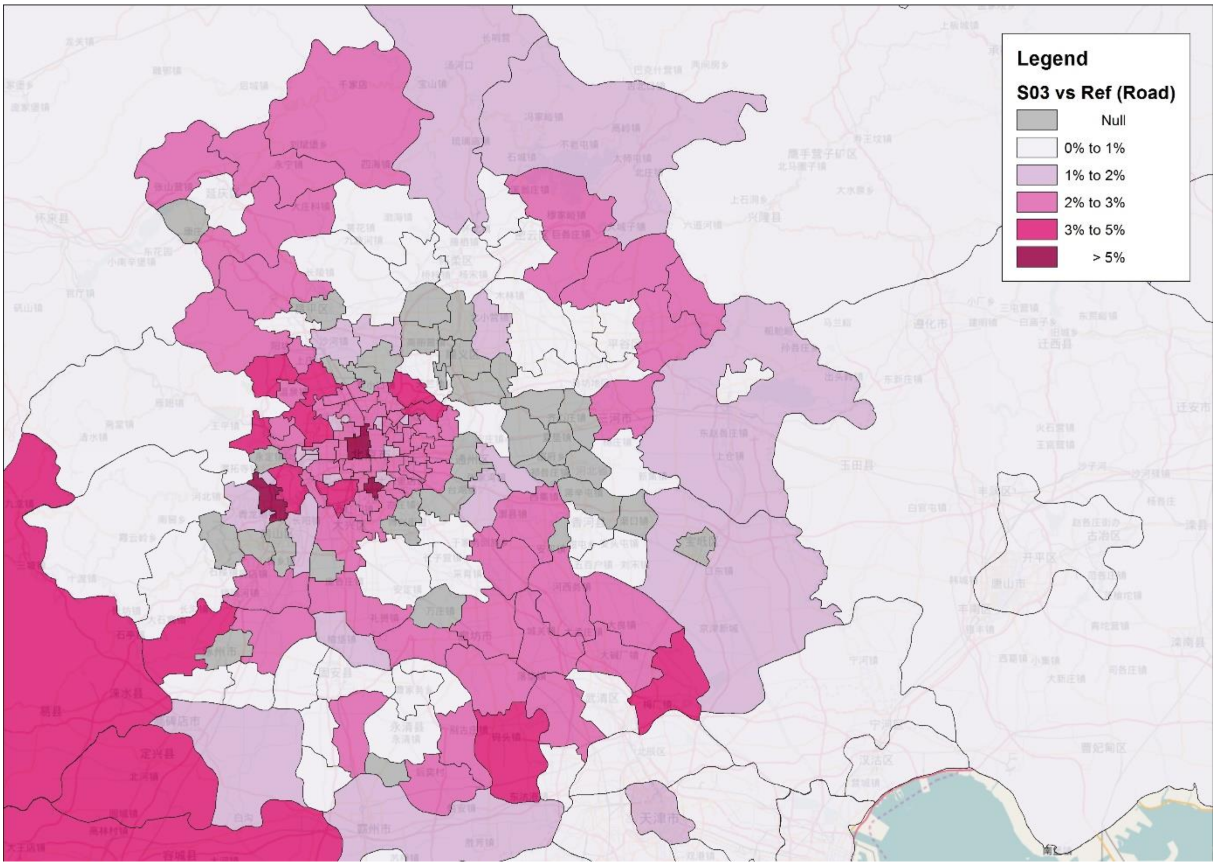


FIGURE 5.7. Road traffic comparison: S03 vs Reference Case

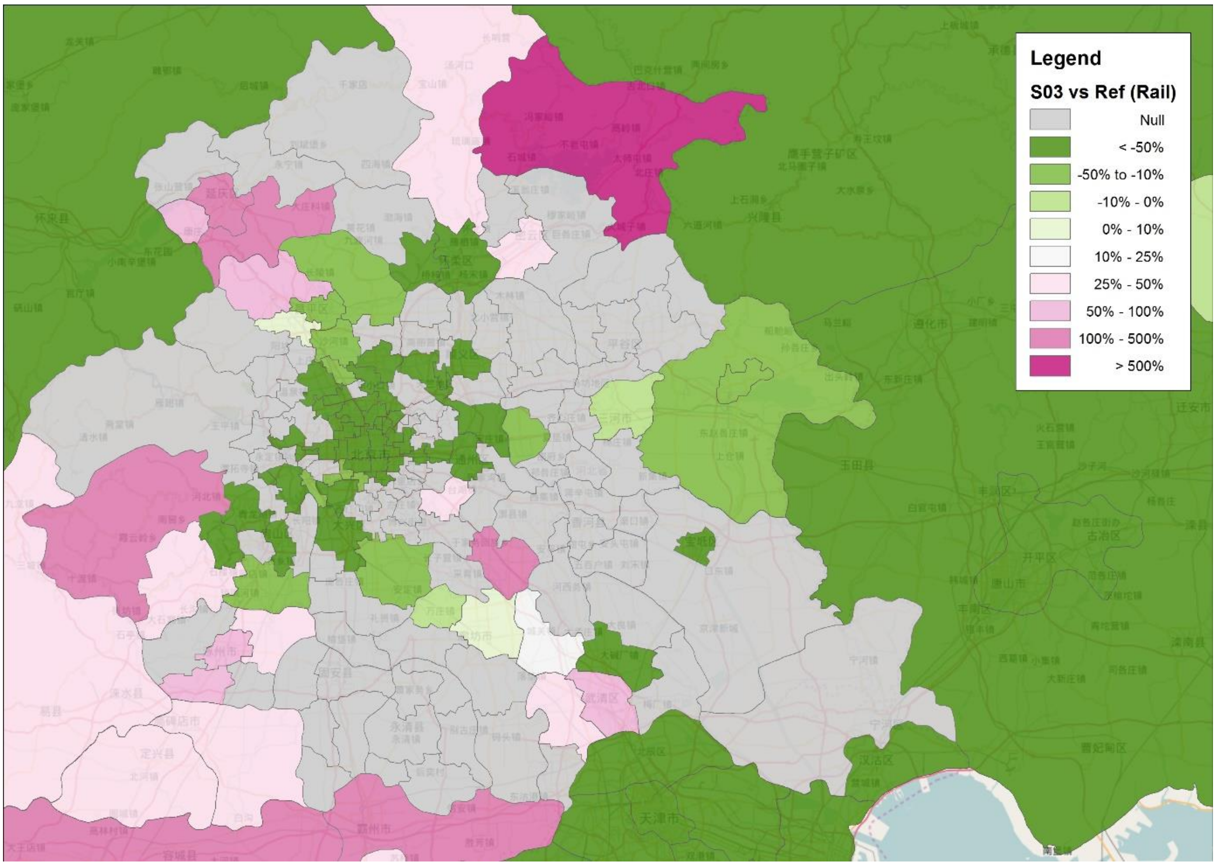


Figure 5.8. Rail traffic comparison: S03 vs Reference Case

5.3.5. Test 4 – S04

Table 5.9 summarize modal split results for **S04**. Although the four districts (which are now combined into expanded Dongcheng and Xicheng districts) in central Beijing are very small in area, the increased car access and parking times to and from this area under **S04** has had a remarkable effect, cutting the car traffic volume inside Beijing's sixth ring road by 8% and car trip-km by 5%. Since this area is well served by all modes of transport, all non-car modes have gained share. Because the central Beijing districts have a relatively high-income profile, the impacts are felt most by the higher income groups (**Appendix 5 - Table A5.4**).

Table 5.9. Summary by trip purpose and mode: S04 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	*All*	*9.3*	*257.2*	*43.6*	*12.8*	*11,264*	*104,913*	*0%*	*-4%*	*1%*	*-1%*	*0%*	*0%*
	Car	9.4	420.6	41.4	13.6	5,051	47,540	2%	1%	3%	-1%	-9%	-7%
	Bus	6.1	100.6	42.7	8.5	2,744	16,665	-1%	0%	0%	-1%	9%	7%
	Walk	1.4	0.0	18.5	4.5	1,309	1,815	1%	-	1%	0%	8%	8%
	Cycle	2.6	0.0	26.0	5.9	551	1,422	0%	-	0%	0%	9%	9%
	Metro/rail	23.3	308.4	77.9	17.9	1,609	37,472	-2%	0%	-1%	-1%	7%	6%
School	*All*	*5.7*	*158.9*	*37.8*	*9.0*	*2,605*	*14,810*	*0%*	*-3%*	*0%*	*0%*	*0%*	*0%*
	Car	6.1	283.3	38.7	9.5	978	6,007	1%	1%	1%	0%	-7%	-5%
	Bus	5.7	100.6	41.5	8.2	877	4,983	-1%	0%	0%	0%	4%	4%
	Walk	1.4	0.0	18.4	4.5	400	548	0%	-	0%	0%	4%	4%
	Cycle	2.5	0.0	25.5	5.8	169	420	0%	-	0%	0%	5%	5%
	Metro/rail	15.8	270.3	70.2	13.5	180	2,853	-1%	0%	0%	-1%	6%	4%
Business	*All*	*18.2*	*710.2*	*50.6*	*21.6*	*342*	*6,243*	*0%*	*-1%*	*4%*	*-4%*	*0%*	*0%*
	Car	21.5	936.6	52.2	24.7	237	5,092	3%	2%	6%	-3%	-4%	-2%
	Bus	6.1	100.6	43.5	8.4	35	211	-2%	0%	-1%	-1%	13%	11%
	Walk	1.6	0.0	20.8	4.5	27	42	1%	-	1%	0%	11%	12%
	Cycle	2.8	0.0	27.3	6.1	8	21	0%	-	0%	0%	12%	12%
	Metro/rail	24.4	483.1	74.5	19.7	36	876	-2%	-2%	-1%	-2%	9%	6%
Other	*All*	*10.1*	*205.6*	*42.4*	*14.3*	*14,228*	*143,649*	*0%*	*-2%*	*1%*	*-1%*	*0%*	*0%*
	Car	14.2	364.0	44.2	19.3	5,657	80,231	3%	3%	2%	1%	-7%	-4%
	Bus	6.2	100.6	42.9	8.6	3,822	23,556	-1%	0%	0%	0%	5%	5%
	Walk	1.7	0.0	21.8	4.6	2,491	4,139	1%	-	0%	0%	4%	5%
	Cycle	2.6	0.0	26.2	6.0	699	1,822	1%	-	0%	0%	5%	6%
	Metro/rail	21.8	308.9	74.9	17.4	1,558	33,901	-2%	-1%	-1%	-1%	9%	7%
All	*All*	*9.5*	*227.8*	*42.5*	*13.4*	*28,439*	*269,615*	*0%*	*-3%*	*1%*	*-1%*	*0%*	*0%*
	Car	11.6	392.8	42.7	16.4	11,923	138,869	3%	2%	3%	0%	-8%	-5%
	Bus	6.1	100.6	42.7	8.5	7,478	45,415	-1%	0%	0%	-1%	6%	5%
	Walk	1.5	0.0	20.4	4.5	4,228	6,544	0%	-	0%	0%	5%	6%
	Cycle	2.6	0.0	26.1	5.9	1,427	3,685	0%	-	0%	0%	6%	7%
	Metro/rail	22.2	308.5	76.1	17.5	3,383	75,101	-2%	0%	-1%	-1%	8%	6%

The road traffic comparison map (**Figure 5.9**) below shows that car traffic volume reduces by 50-75% in the central Beijing districts, although the impacts are fairly local. The rail traffic comparison map (**Figure 5.10**) shows that rail and metro gain marginally (<5%) in most areas around the districts, with the southwest corridor gaining the most, by 10-25%.

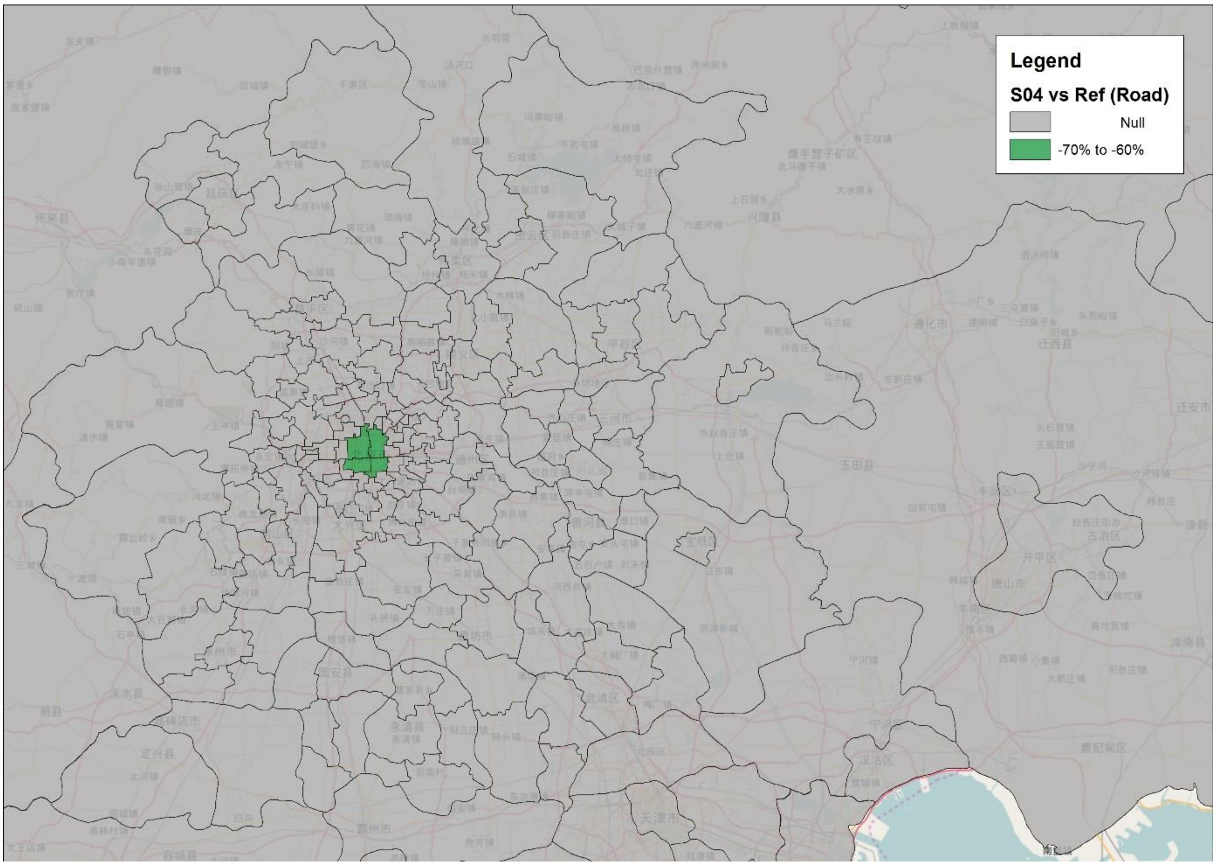


FIGURE 5.9. Road traffic comparison: S04 vs Reference Case

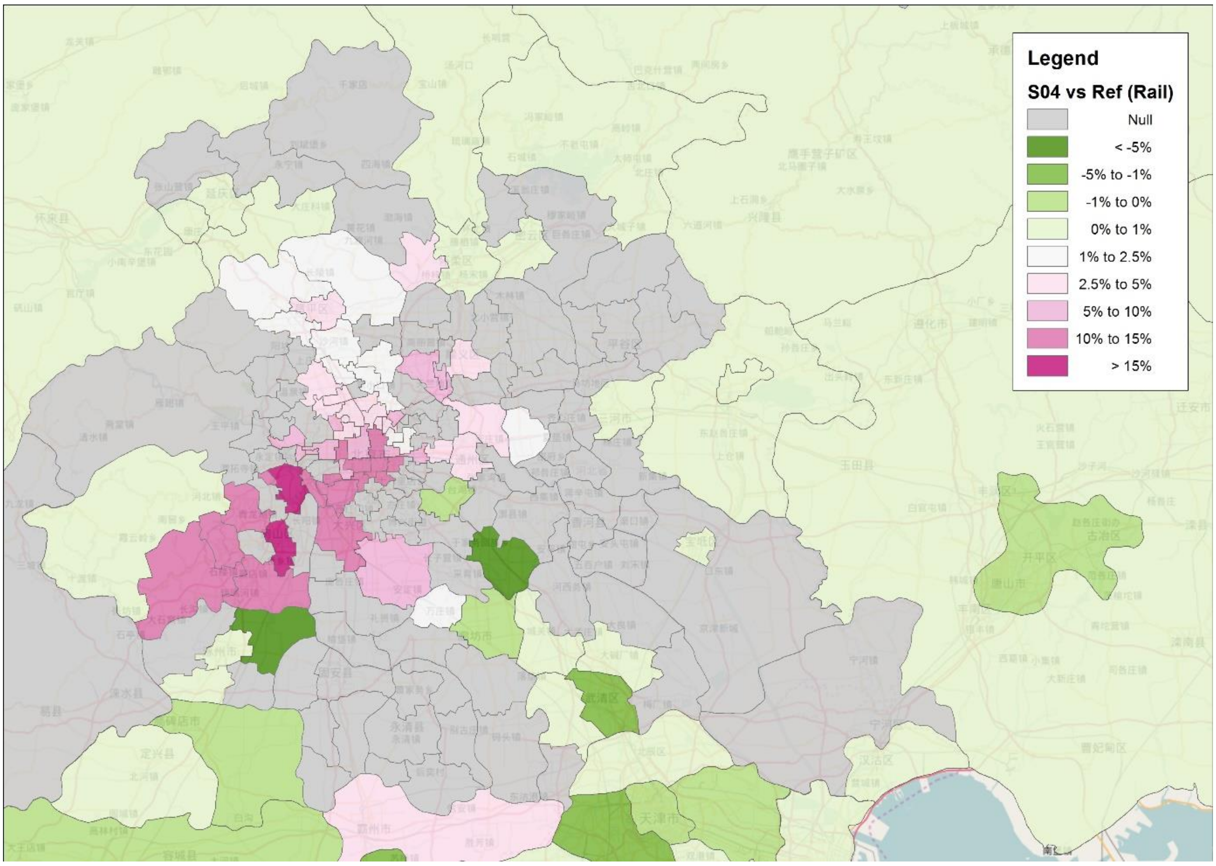


Figure 5.10. Rail traffic comparison: S04 vs Reference Case

5.3.6. Test 5 – S05

S05 highlights the need to improve the access/egress and boarding/alighting times to/from bus services. **Table 5.10** summarize modal split for S05. As expected S05 does not alter the overall trip volume, but increases the total trip-km by 2%. There is a sharp increase in bus patronage (by 91%) and bus trip-km (by 93%). The impacts are felt almost equally by all income groups (**Appendix 5 - Table A5.5**). Naturally, all non-bus modes lose mode share, but metro/rail loses the least (by 15%), followed by car (31%), indicating that metro and, to a more limited extent, car are not really in great competition among the transport corridors. The results suggest that it is the areas that currently are not served well by metro and rail that would require urgent attention. Also, the improved bus services would reduce those walking and cycling by more than a third (36% and 38% respectively) when compared with the reference case, where walking and cycling are already low.

Table 5.10. Summary by trip purpose and mode: S05 vs Reference Case

Scenario tests								Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	*All*	*9.5*	*243.6*	*39.8*	*14.3*	*11,264*	*106,933*	*2%*	*-9%*	*-7%*	*10%*	*0%*	*2%*
	Car	10.9	483.3	41.1	15.9	3,788	41,298	18%	16%	2%	16%	-31%	-19%
	Bus	6.3	100.6	33.0	11.4	5,063	31,705	2%	0%	-23%	32%	101%	104%
	Walk	1.3	0.0	18.0	4.5	803	1,076	-3%	-	-2%	0%	-34%	-36%
	Cycle	2.6	0.0	26.0	5.9	322	826	0%	-	0%	0%	-37%	-37%
	Metro/rail	24.9	313.7	79.4	18.8	1,289	32,029	5%	2%	1%	4%	-14%	-10%
School	*All*	*6.0*	*147.9*	*33.3*	*10.8*	*2,605*	*15,558*	*5%*	*-9%*	*-12%*	*19%*	*0%*	*5%*
	Car	6.9	313.6	38.3	10.9	626	4,341	15%	12%	0%	14%	-40%	-32%
	Bus	5.5	100.6	31.0	10.7	1,516	8,386	-3%	0%	-25%	30%	81%	74%
	Walk	1.3	0.0	17.7	4.4	239	314	-4%	-	-3%	0%	-38%	-40%
	Cycle	2.4	0.0	25.2	5.8	95	231	-2%	-	-1%	-1%	-41%	-42%
	Metro/rail	17.8	285.1	71.4	15.0	128	2,286	11%	5%	1%	10%	-25%	-16%
Business	*All*	*18.2*	*696.1*	*47.1*	*23.2*	*342*	*6,237*	*0%*	*-3%*	*-3%*	*3%*	*0%*	*0%*
	Car	22.8	988.8	50.2	27.2	218	4,966	9%	8%	2%	6%	-12%	-4%
	Bus	6.4	100.6	33.5	11.4	68	431	2%	0%	-24%	34%	121%	126%
	Walk	1.6	0.0	20.6	4.5	20	31	0%	-	0%	0%	-17%	-17%
	Cycle	2.9	0.0	27.7	6.2	6	16	2%	-	1%	1%	-17%	-15%
	Metro/rail	25.8	507.0	75.7	20.5	31	793	3%	3%	1%	2%	-7%	-4%
Other	*All*	*10.3*	*204.1*	*38.8*	*16.0*	*14,228*	*146,963*	*2%*	*-2%*	*-8%*	*11%*	*0%*	*2%*
	Car	16.7	423.5	44.7	22.4	4,323	72,118	22%	20%	3%	18%	-29%	-14%
	Bus	6.2	100.6	32.8	11.4	6,796	42,423	1%	0%	-23%	32%	87%	88%
	Walk	1.6	0.0	21.0	4.6	1,490	2,382	-3%	-	-3%	0%	-37%	-40%
	Cycle	2.6	0.0	26.1	5.9	405	1,047	0%	-	0%	0%	-39%	-39%
	Metro/rail	23.9	320.8	76.8	18.7	1,214	28,993	8%	3%	2%	6%	-15%	-9%
All	*All*	*9.7*	*220.5*	*38.8*	*15.0*	*28,439*	*275,692*	*2%*	*-6%*	*-8%*	*11%*	*0%*	*2%*
	Car	13.7	454.9	42.9	19.2	8,954	122,723	21%	18%	3%	18%	-31%	-16%
	Bus	6.2	100.6	32.7	11.3	13,444	82,944	1%	0%	-24%	32%	91%	93%
	Walk	1.5	0.0	19.8	4.5	2,552	3,804	-3%	-	-3%	0%	-36%	-38%
	Cycle	2.6	0.0	26.0	5.9	828	2,120	0%	-	0%	0%	-38%	-39%
	Metro/rail	24.1	317.8	77.8	18.6	2,661	64,101	7%	3%	2%	5%	-15%	-9%

The road traffic comparison map (**Figure 5.11**) below shows that road traffic volume could reduce by 30-40% in most areas, with small islands in the near suburbs of Beijing reducing by 20-30%. The rail traffic comparison map (**Figure 5.12**) shows that the main areas where metro and rail lose share are the built up areas of Beijing and associated suburban commuter corridors from the southwest, northwest, east and southeast.

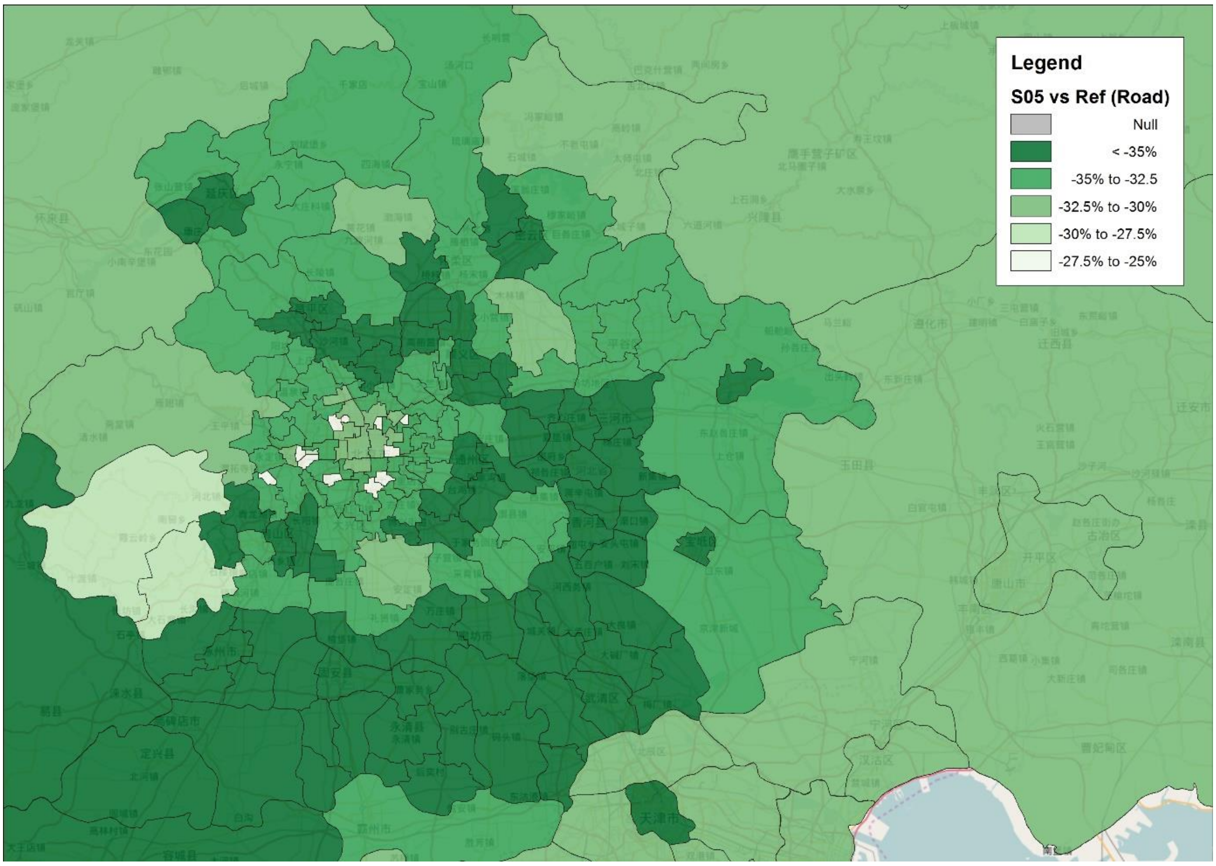


Figure 5.11. Road traffic comparison: S05 vs Reference Case

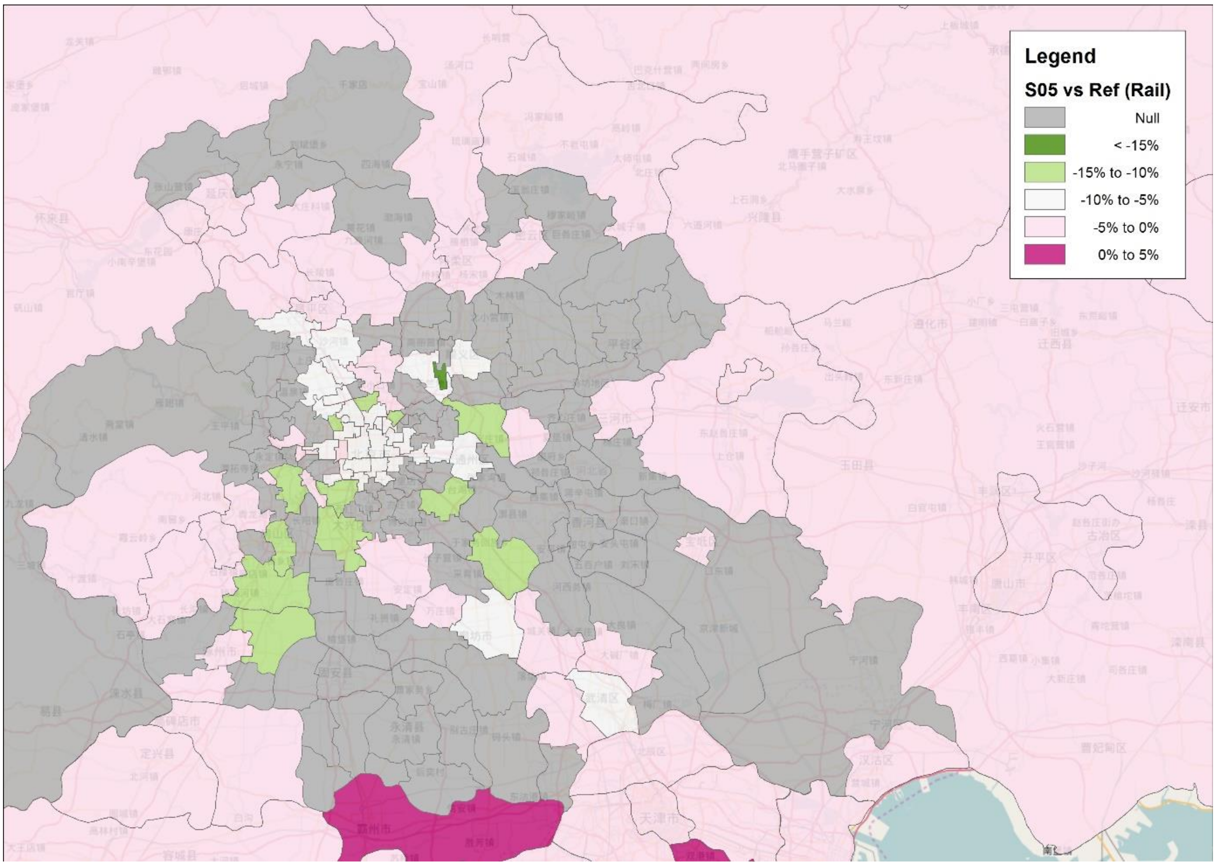


Figure 5.12. Rail traffic comparison: S05 vs Reference Case

5.3.7. Test 6 – S06

Under **S06** both bus and metro access/egress times have improved**. Table 5.11** summarize modal split results by all purposes for S06. As a result, the total trip-km is raised by 3%. There is a less sharp increase in bus patronage (by 83%) and bus trip-km (by 79%) in comparison with S05 (91% and 93% respectively in S05), and metro gains mode share by 40%. The impacts are felt almost equally by all income groups for bus, and for metro the impacts are larger for the higher income groups (**Appendix 5 - Table A5.6**). Naturally, all non-bus/metro modes lose mode share, and this exacerbate the loss of mode share for walking and cycling.

Table 5.11. Summary by trip purpose and mode: S06 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	*All*	*9.5*	*224.9*	*39.3*	*14.6*	*11,264*	*107,504*	*2%*	*-16%*	*-8%*	*12%*	*0%*	*2%*
	Car	10.0	441.3	40.5	14.8	3,368	33,534	8%	6%	1%	7%	-39%	-34%
	Bus	6.0	100.6	32.2	11.1	4,800	28,686	-3%	0%	-25%	30%	90%	85%
	Walk	1.3	0.0	17.8	4.5	781	1,032	-4%	-	-3%	-1%	-36%	-38%
	Cycle	2.5	0.0	25.6	5.9	309	771	-3%	-	-2%	-1%	-39%	-41%
	Metro/rail	21.7	281.1	65.0	20.0	2,007	43,481	-8%	-9%	-17%	10%	34%	23%
School	*All*	*6.1*	*145.0*	*33.6*	*10.8*	*2,605*	*15,800*	*7%*	*-11%*	*-11%*	*20%*	*0%*	*7%*
	Car	6.4	292.9	38.0	10.2	581	3,738	6%	4%	0%	7%	-45%	-41%
	Bus	5.5	100.5	30.8	10.7	1,459	7,986	-4%	0%	-26%	29%	74%	66%
	Walk	1.3	0.0	17.6	4.4	233	303	-5%	-	-4%	-1%	-40%	-42%
	Cycle	2.4	0.0	25.0	5.7	92	220	-3%	-	-2%	-2%	-43%	-45%
	Metro/rail	14.8	253.8	58.5	15.2	240	3,553	-8%	-6%	-17%	11%	41%	30%
Business	*All*	*18.3*	*668.6*	*46.9*	*23.3*	*342*	*6,249*	*0%*	*-7%*	*-3%*	*4%*	*0%*	*0%*
	Car	22.9	991.4	50.4	27.3	204	4,682	10%	8%	3%	7%	-18%	-9%
	Bus	6.3	100.6	33.1	11.4	65	404	0%	0%	-25%	34%	111%	112%
	Walk	1.5	0.0	20.3	4.5	20	30	-2%	-	-2%	0%	-19%	-21%
	Cycle	2.8	0.0	27.1	6.1	5	15	-1%	-	-1%	-1%	-20%	-21%
	Metro/rail	23.1	407.0	63.8	21.7	48	1,119	-8%	-17%	-15%	9%	47%	36%
Other	*All*	*10.4*	*196.7*	*38.9*	*16.1*	*14,228*	*147,981*	*3%*	*-6%*	*-7%*	*11%*	*0%*	*3%*
	Car	16.0	406.0	44.3	21.7	3,801	60,925	17%	15%	3%	14%	-38%	-27%
	Bus	6.1	100.6	32.5	11.3	6,499	39,826	-1%	0%	-24%	31%	79%	77%
	Walk	1.6	0.0	20.9	4.6	1,450	2,298	-4%	-	-4%	-1%	-39%	-42%
	Cycle	2.5	0.0	25.7	5.9	388	978	-3%	-	-2%	-1%	-42%	-43%
	Metro/rail	21.0	287.8	63.7	19.8	2,089	43,955	-5%	-7%	-15%	12%	46%	38%
All	*All*	*9.8*	*208.8*	*38.7*	*15.1*	*28,439*	*277,534*	*3%*	*-11%*	*-8%*	*12%*	*0%*	*3%*
	Car	12.9	427.7	42.4	18.3	7,954	102,878	14%	11%	2%	12%	-38%	-30%
	Bus	6.0	100.6	32.2	11.2	12,823	76,901	-2%	0%	-25%	30%	83%	79%
	Walk	1.5	0.0	19.6	4.5	2,483	3,663	-4%	-	-4%	-1%	-38%	-41%
	Cycle	2.5	0.0	25.6	5.8	795	1,984	-3%	-	-2%	-1%	-41%	-42%
	Metro/rail	21.0	284.2	64.0	19.7	4,385	92,108	-7%	-8%	-16%	11%	40%	30%

Unsurprisingly, the road traffic comparison map (**Figure 5.13**) is very similar to that for S05, but the rail traffic comparison map (**Figure 5.14**) confirms that the central built up areas of Beijing and Tianjin and associated near suburban commuter corridors gain variously mode share between 25% up to 75%. This also diverts traffic from rail to combinations of metro and intercity buses, indicating that the main challenge for regional rail and high speed rail is locally access to diffused origins and destinations in the city region.

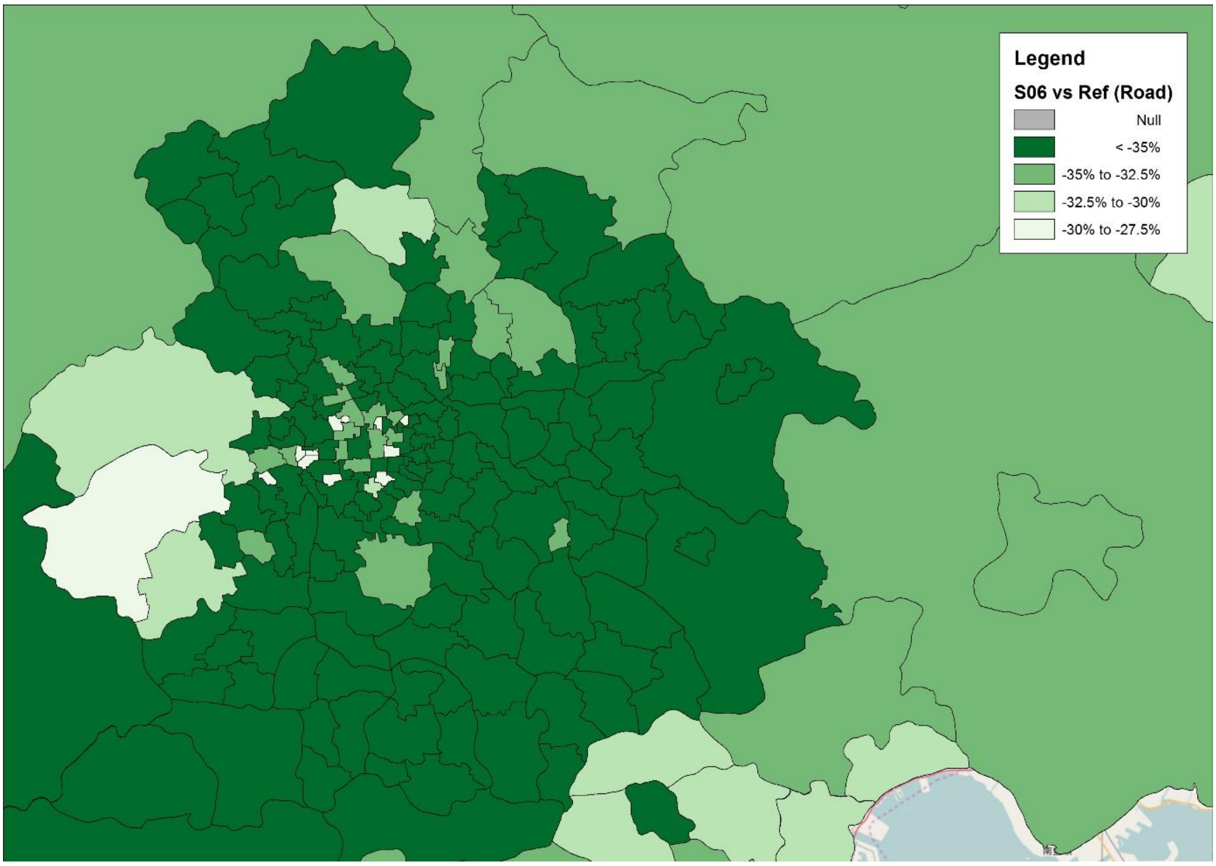


Figure 5.13. Road traffic comparison: S06 vs Reference Case

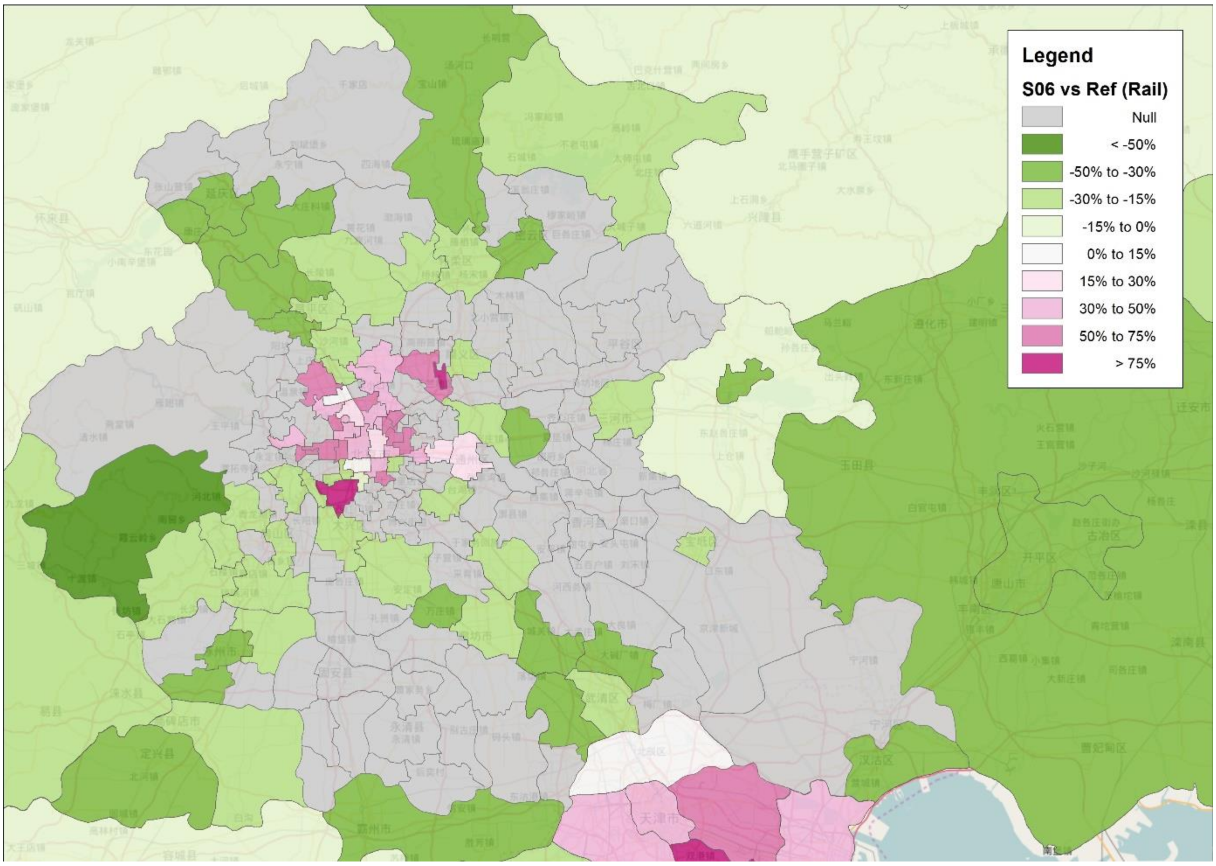


Figure 5.14. Rail traffic comparison: S06 vs Reference Case

5.4. Medium term impacts of strategic transport interventions

5.4.1. Overview

We then repeat the same six tests for medium term effects, where the total zonal values of jobs, housing and households are kept the same, and the trips may be redistributed among the OD zone pairs. As such we expect to see more adaptations by employers and residents in travel. We summarise the results by presenting the summary data tables and road and rail traffic maps in the same format. To differentiate the tests, we add a lower-case letter ‘r’ to S01-S06 (e.g. rS01), for the medium-term effect tests.

Table 5.12. Summary by mode: Scenario rS01 – rS06 vs Reference Case

Scenario tests								Percentage changes from reference case					
Scenario	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
rS01	*All*	*9*	*235*	*42*	*12*	*28,420*	*242,272*	*-10%*	*0%*	*1%*	*-11%*	*0%*	*-10%*
	Car	8	464	39	13	9,666	78,501	-28%	20%	-7%	-23%	-25%	-46%
	Bus	6	101	43	9	8,445	54,122	5%	0%	2%	3%	20%	26%
	Walk	2	0	21	5	4,598	7,185	1%	-	1%	0%	15%	16%
	Cycle	3	0	26	6	1,561	4,086	2%	-	1%	1%	16%	18%
	Metro/rail	24	325	78	18	4,151	98,377	5%	5%	3%	2%	32%	39%
rS02	*All*	*10*	*196*	*42*	*13*	*28,433*	*270,301*	*0%*	*-16%*	*1%*	*-1%*	*0%*	*0%*
	Car	12	402	42	17	11,506	136,123	5%	4%	1%	4%	-11%	-7%
	Bus	6	0	42	9	9,196	55,452	-2%	-100%	-1%	-1%	31%	29%
	Walk	2	0	20	5	3,525	5,373	-1%	-	-1%	0%	-12%	-13%
	Cycle	3	0	26	6	1,164	2,980	0%	-	0%	0%	-13%	-14%
	Metro/rail	23	307	77	18	3,042	70,373	3%	-1%	0%	2%	-3%	-1%
rS03	*All*	*10*	*196*	*42*	*13*	*28,433*	*270,301*	*0%*	*-16%*	*1%*	*-1%*	*0%*	*0%*
	Car	12	402	42	17	11,506	136,123	5%	4%	1%	4%	-11%	-7%
	Bus	6	0	42	9	9,196	55,452	-2%	-100%	-1%	-1%	31%	29%
	Walk	2	0	20	5	3,525	5,373	-1%	-	-1%	0%	-12%	-13%
	Cycle	3	0	26	6	1,164	2,980	0%	-	0%	0%	-13%	-14%
	Metro/rail	23	307	77	18	3,042	70,373	3%	-1%	0%	2%	-3%	-1%
rS04	*All*	*9*	*227*	*42*	*13*	*28,437*	*268,789*	*0%*	*-3%*	*1%*	*-1%*	*0%*	*0%*
	Car	12	392	43	16	11,918	138,454	3%	2%	2%	0%	-8%	-5%
	Bus	6	101	43	9	7,487	45,415	-1%	0%	0%	-1%	7%	5%
	Walk	2	0	20	5	4,238	6,559	0%	-	0%	0%	6%	6%
	Cycle	3	0	26	6	1,430	3,689	0%	-	0%	0%	7%	7%
	Metro/rail	22	308	76	17	3,365	74,672	-2%	-1%	-1%	-1%	7%	6%
rS05	*All*	*9*	*213*	*38*	*15*	*28,420*	*265,879*	*-1%*	*-9%*	*-9%*	*8%*	*0%*	*-1%*
	Car	13	442	43	19	8,788	115,488	16%	15%	2%	14%	-32%	-21%
	Bus	6	101	33	11	13,636	83,836	0%	0%	-24%	32%	94%	95%
	Walk	1	0	20	5	2,602	3,877	-3%	-	-3%	0%	-35%	-37%
	Cycle	3	0	26	6	841	2,144	-1%	-	0%	0%	-37%	-38%
	Metro/rail	24	316	77	18	2,553	60,533	5%	2%	1%	4%	-19%	-14%
rS06	*All*	*10*	*206*	*39*	*15*	*28,441*	*276,263*	*2%*	*-12%*	*-8%*	*11%*	*0%*	*2%*
	Car	13	419	42	18	7,841	98,382	11%	9%	1%	10%	-39%	-33%
	Bus	6	101	32	11	12,797	76,988	-2%	0%	-25%	30%	82%	79%
	Walk	1	0	20	5	2,470	3,648	-4%	-	-4%	-1%	-38%	-41%
	Cycle	3	0	26	6	792	1,985	-3%	-	-1%	-1%	-41%	-42%
	Metro/rail	21	282	64	20	4,541	95,260	-7%	-9%	-17%	12%	45%	35%

Table 5.12 represents the overall results of the strategic transport intervention scenario in these medium-term tests rS01 – rS06. The more detailed summaries can be found in the following subsections and in **Appendix 6**.

5.4.2. Test 7 – rS01

Table 5.13 summarizes modal split results by all purposes for **rS01**. As expected rS01 does not alter the overall trip volume, but it reduces the total trip-km by 10%. There is an even higher reduction in car trip volume (by 25.%) and car trip-km (by 46%). The impacts are again felt most by the low-income groups, although the higher income groups also adapt to the increase of car costs (**Appendix 6 - Table A6.1**). All non-car modes gain mode share, although the redistribution of the trips has also made the losses smaller. For instance, the metro services that gain trip volume by 32% (401% under S01) and trip-km by 39% (56% under S01).

Table 5.13. Summary by trip purpose and mode: rS01 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	*All*	*9.1*	*267.9*	*44.0*	*12.4*	*11,264*	*102,277*	*-2%*	*0%*	*2%*	*-5%*	*0%*	*-2%*
	Car	7.3	484.0	38.2	11.4	4,290	31,181	-21%	17%	-5%	-17%	-22%	-39%
	Bus	6.5	100.6	43.8	8.9	3,033	19,627	5%	0%	2%	3%	20%	27%
	Walk	1.4	0.0	18.7	4.5	1,377	1,931	2%	-	2%	0%	13%	15%
	Cycle	2.6	0.0	26.3	6.0	589	1,551	2%	-	1%	1%	16%	19%
	Metro/rail	24.3	321.8	79.6	18.3	1,974	47,986	3%	4%	2%	1%	32%	35%
School	*All*	*5.3*	*163.6*	*37.4*	*8.6*	*2,605*	*13,891*	*-6%*	*0%*	*-1%*	*-6%*	*0%*	*-6%*
	Car	4.8	328.9	36.6	7.9	836	4,048	-20%	17%	-4%	-17%	-20%	-36%
	Bus	5.8	100.6	41.7	8.3	963	5,568	1%	0%	0%	1%	15%	16%
	Walk	1.4	0.0	18.5	4.5	426	587	1%	-	1%	0%	11%	12%
	Cycle	2.5	0.0	25.6	5.9	182	455	1%	-	1%	0%	12%	14%
	Metro/rail	16.3	274.7	71.1	13.8	198	3,232	2%	1%	1%	1%	16%	18%
Business	*All*	*16.1*	*824.3*	*47.6*	*20.3*	*341*	*5,504*	*-12%*	*15%*	*-2%*	*-10%*	*0%*	*-12%*
	Car	16.5	1069.4	45.7	21.6	226	3,730	-21%	17%	-7%	-15%	-9%	-28%
	Bus	6.7	100.7	45.0	9.0	37	251	8%	0%	3%	5%	22%	32%
	Walk	1.6	0.0	20.8	4.5	28	43	1%	-	1%	0%	14%	15%
	Cycle	2.8	0.0	27.6	6.2	8	22	1%	-	1%	1%	16%	17%
	Metro/rail	34.3	839.4	80.5	25.5	43	1,457	37%	71%	7%	28%	29%	77%
Other	*All*	*8.5*	*208.0*	*41.9*	*12.2*	*14,209*	*120,600*	*-16%*	*-1%*	*0%*	*-16%*	*0%*	*-16%*
	Car	9.2	437.8	39.6	13.9	4,313	39,542	-33%	24%	-9%	-27%	-29%	-53%
	Bus	6.5	100.7	43.6	8.9	4,411	28,676	5%	0%	2%	3%	21%	27%
	Walk	1.7	0.0	21.9	4.6	2,767	4,623	1%	-	1%	0%	16%	17%
	Cycle	2.6	0.0	26.4	6.0	781	2,058	2%	-	1%	1%	18%	19%
	Metro/rail	23.6	321.8	78.1	18.1	1,936	45,701	7%	4%	4%	3%	35%	44%
All	*All*	*8.5*	*235.1*	*42.4*	*12.1*	*28,420*	*242,272*	*-10%*	*0%*	*1%*	*-11%*	*0%*	*-10%*
	Car	8.1	463.7	38.8	12.5	9,666	78,501	-28%	20%	-7%	-23%	-25%	-46%
	Bus	6.4	100.6	43.5	8.8	8,445	54,122	5%	0%	2%	3%	20%	26%
	Walk	1.6	0.0	20.6	4.6	4,598	7,185	1%	-	1%	0%	15%	16%
	Cycle	2.6	0.0	26.3	6.0	1,561	4,086	2%	-	1%	1%	16%	18%
	Metro/rail	23.7	324.9	78.5	18.1	4,151	98,377	5%	5%	3%	2%	32%	39%

The road traffic comparison map (**Figure 5.15**) below shows that road traffic volume (measured in pcu's on road) reduces by 30-40% in the areas outside the main built up area of Beijing. The area where the reduction is somewhat lower, ranging from 10-30% (which is in and around the main built up area of Beijing) has spread relative to rS01. Similarly the rail traffic comparison map (**Figure 5.16**) shows that rail and metro gain considerably less than under S01.

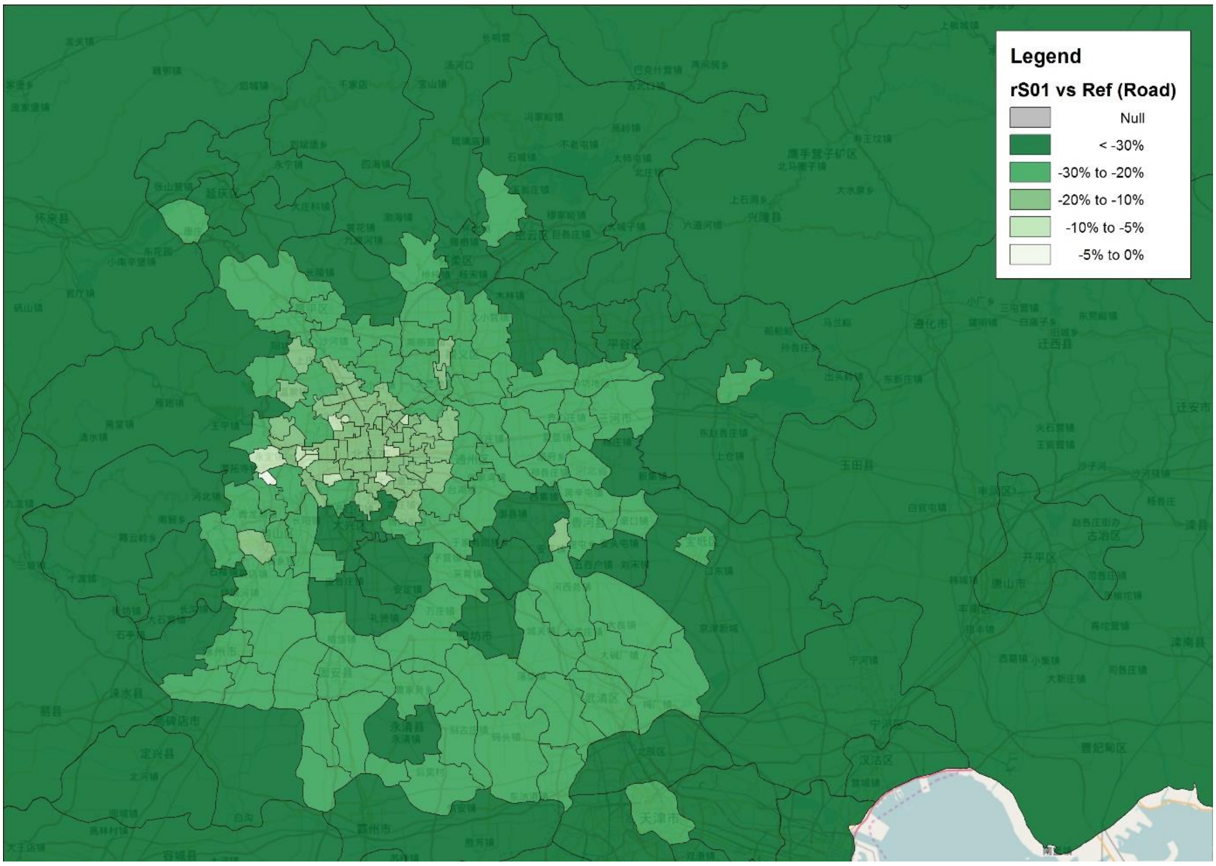


FIGURE 5.15. Road traffic comparison: rS01 vs Reference Case

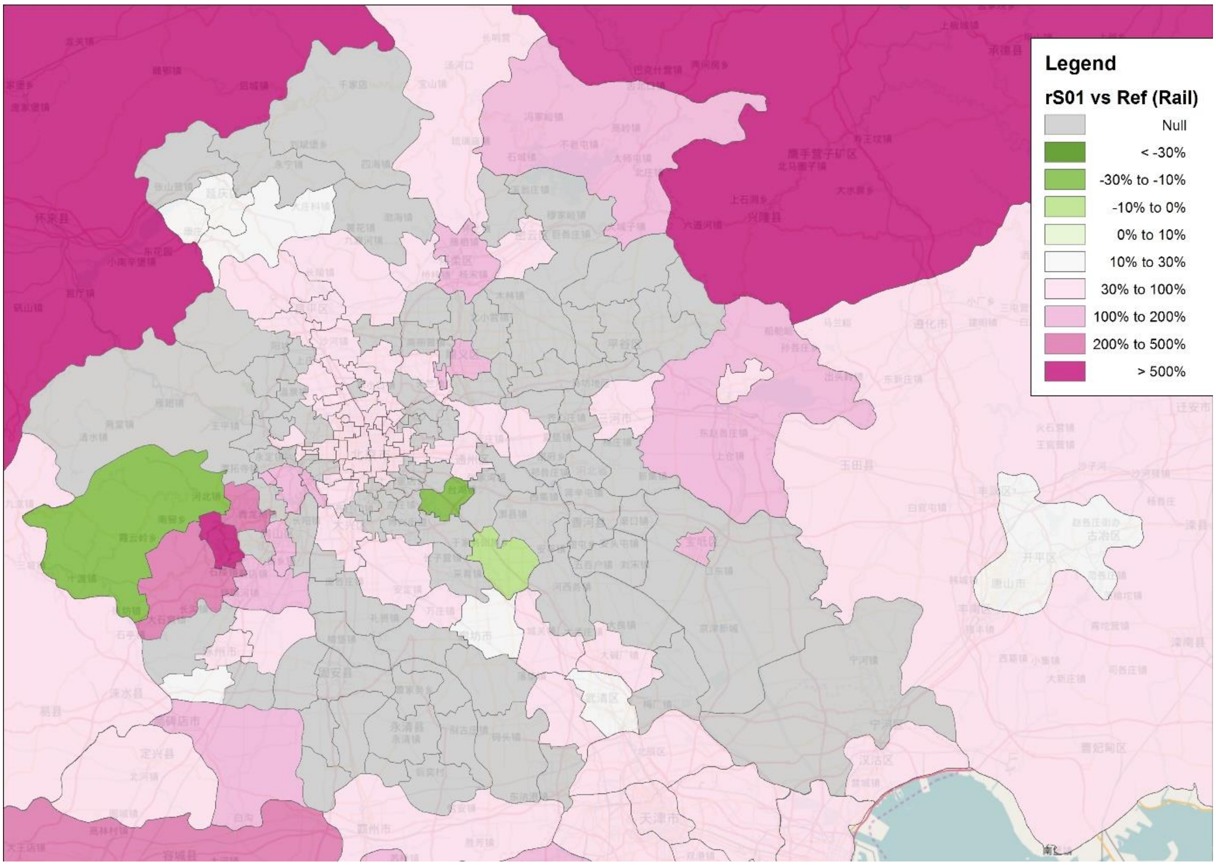


Figure 5.16. Rail traffic comparison: rS01 vs Reference Case

5.4.3. Test 8 – rS02

Unlike rS01 above, under **rS02** there is less scope for adaptation and the model results are quite similar to those of S02. We include the summary tables (**Table 5.14** and **Appendix 6 - Table A6.2**) and the road and rail comparison maps (**Figure 5.17** and **Figure 5.18**) for information only.

Table 5.14. Summary by trip purpose and mode: rS02 vs Reference Case

Scenario tests								Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	***All***	***9.4***	***228.8***	***43.4***	***13.0***	***11,264***	***106,094***	***1%***	***-14%***	***1%***	***0%***	***0%***	***1%***
	Car	9.7	434.0	40.5	14.3	4,902	47,373	5%	4%	1%	4%	-11%	-7%
	Bus	6.1	0.0	42.7	8.5	3,389	20,539	-2%	-100%	-1%	-1%	34%	32%
	Walk	1.4	0.0	18.3	4.5	1,066	1,454	-1%	-	-1%	0%	-12%	-13%
	Cycle	2.6	0.0	26.0	5.9	438	1,124	0%	-	0%	0%	-14%	-14%
	Metro/rail	24.2	305.9	78.3	18.6	1,469	35,604	2%	-1%	0%	2%	-2%	0%
School	***All***	***5.8***	***115.6***	***38.1***	***9.1***	***2,605***	***15,004***	***1%***	***-29%***	***1%***	***0%***	***0%***	***1%***
	Car	6.2	286.5	38.1	9.8	902	5,592	2%	2%	0%	2%	-14%	-12%
	Bus	5.6	0.0	41.3	8.2	1,071	6,015	-2%	-100%	-1%	-1%	28%	25%
	Walk	1.3	0.0	18.1	4.5	336	453	-1%	-	-1%	0%	-13%	-14%
	Cycle	2.5	0.0	25.4	5.8	139	340	-1%	-	0%	0%	-14%	-15%
	Metro/rail	16.5	271.6	70.4	14.1	157	2,603	3%	0%	0%	3%	-8%	-5%
Business	***All***	***18.2***	***701.6***	***48.7***	***22.5***	***342***	***6,237***	***0%***	***-2%***	***0%***	***0%***	***0%***	***0%***
	Car	21.1	921.6	49.1	25.7	243	5,126	1%	1%	0%	1%	-2%	-1%
	Bus	6.2	0.0	43.7	8.5	36	219	-1%	-100%	-1%	0%	16%	15%
	Walk	1.6	0.0	20.6	4.5	24	37	0%	-	0%	0%	-2%	-2%
	Cycle	2.8	0.0	27.4	6.1	7	18	0%	-	0%	0%	-2%	-2%
	Metro/rail	25.2	478.1	75.0	20.2	33	836	1%	-3%	0%	1%	1%	2%
Other	***All***	***10.1***	***171.8***	***42.3***	***14.2***	***14,222***	***142,967***	***0%***	***-18%***	***1%***	***-1%***	***0%***	***0%***
	Car	14.3	369.4	43.5	19.7	5,459	78,032	4%	4%	1%	4%	-11%	-7%
	Bus	6.1	0.0	42.7	8.6	4,701	28,678	-2%	-100%	-1%	-1%	29%	27%
	Walk	1.6	0.0	21.4	4.6	2,098	3,429	-1%	-	-1%	0%	-12%	-13%
	Cycle	2.6	0.0	26.1	5.9	580	1,498	0%	-	0%	0%	-13%	-13%
	Metro/rail	22.7	308.0	75.4	18.0	1,383	31,330	2%	-1%	0%	2%	-4%	-1%
All	***All***	***9.5***	***195.6***	***42.4***	***13.4***	***28,433***	***270,301***	***0%***	***-16%***	***1%***	***-1%***	***0%***	***0%***
	Car	11.8	402.1	41.9	16.9	11,506	136,123	5%	4%	1%	4%	-11%	-7%
	Bus	6.0	0.0	42.5	8.5	9,196	55,452	-2%	-100%	-1%	-1%	31%	29%
	Walk	1.5	0.0	20.2	4.5	3,525	5,373	-1%	-	-1%	0%	-12%	-13%
	Cycle	2.6	0.0	26.0	5.9	1,164	2,980	0%	-	0%	0%	-13%	-14%
	Metro/rail	23.1	306.9	76.6	18.1	3,042	70,373	3%	-1%	0%	2%	-3%	-1%

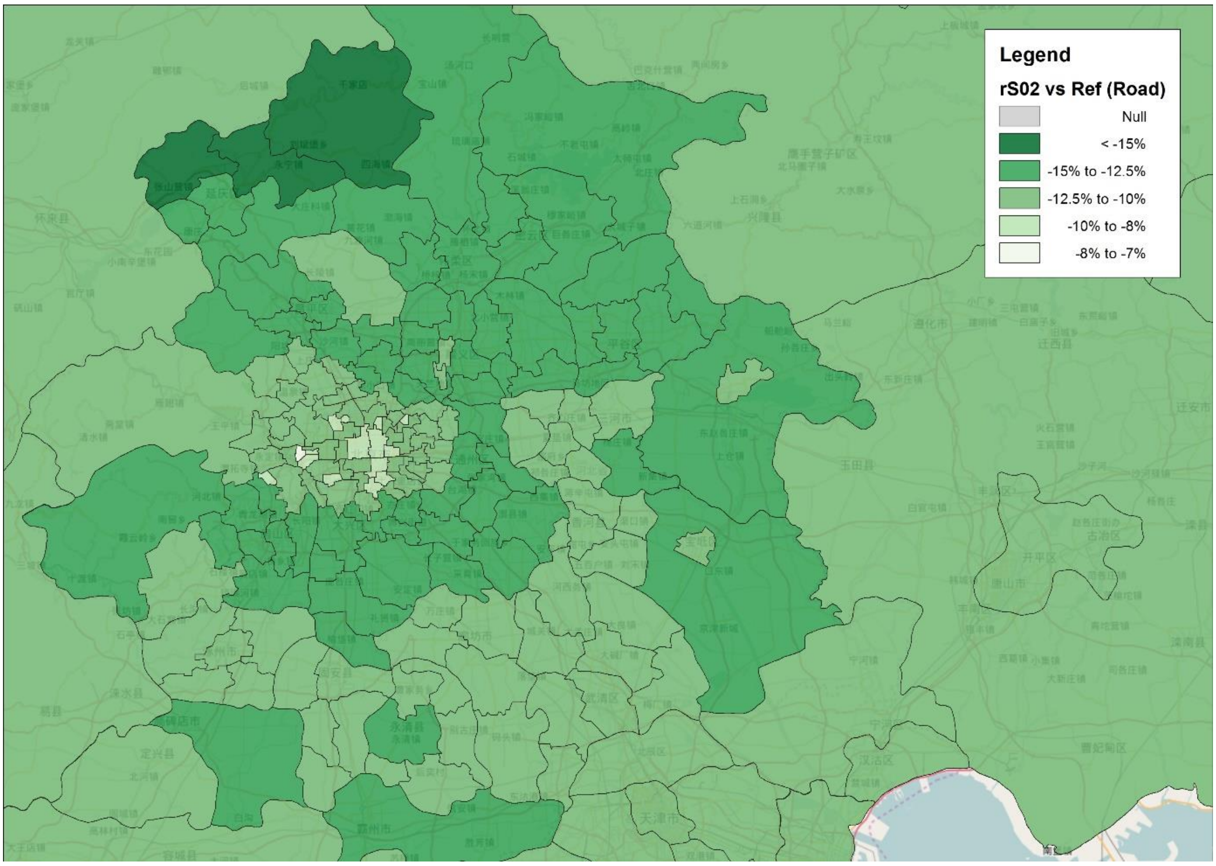


Figure 5.17. Road traffic comparison: rS02 vs Reference Case

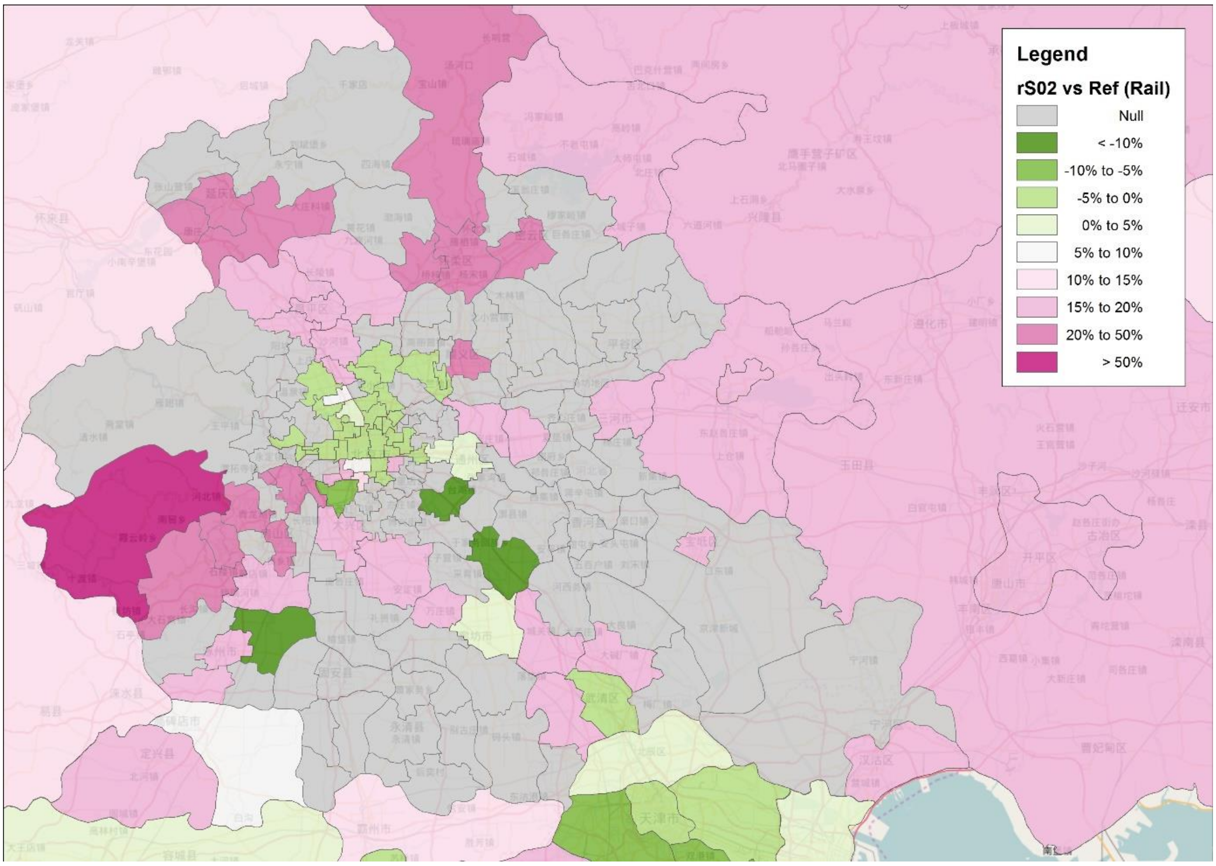


Figure 5.18. Rail traffic comparison: rS02 vs Reference Case

5.4.4. Test 9 – rS03

Similarly, the results under **rS03** are not so different from those under S03, although the total trip-km reduces by 5%. The significant reduction in rail and metro trip volume (by 72%) and trip-km (by 81%) are very similar to those of S03 (71% and 79% respectively in S03). The impacts are also felt most by the low-income groups (**Appendix 6 - Table A6.3**). However, because there are more opportunities to adapt through trip redistribution, the car mode gains considerably less (the trip volume by 12% vs 13% under S03, and trip-km by 24% vs 32% under S03), as shown in **Table 5.15**.

Table 5.15. Summary by trip purpose and mode: rS03 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	*All*	*9.1*	*339.9*	*40.5*	*13.5*	*11,265*	*102,584*	*-2%*	*27%*	*-6%*	*4%*	*0%*	*-2%*
	Car	11.3	498.9	41.8	16.2	6,347	71,495	22%	20%	4%	18%	15%	40%
	Bus	7.6	100.8	46.5	9.8	2,732	20,746	23%	0%	8%	14%	8%	34%
	Walk	1.4	0.0	18.6	4.5	1,244	1,726	1%	-	1%	0%	2%	3%
	Cycle	2.6	0.0	26.4	6.0	524	1,382	3%	-	1%	1%	3%	6%
	Metro/rail	17.3	926.4	64.8	16.0	418	7,235	-27%	200%	-17%	-12%	-72%	-80%
School	*All*	*5.2*	*170.9*	*36.0*	*8.7*	*2,603*	*13,535*	*-9%*	*5%*	*-4%*	*-4%*	*0%*	*-9%*
	Car	6.3	290.5	38.3	9.9	1,108	6,981	4%	4%	0%	4%	6%	10%
	Bus	5.8	100.6	41.7	8.3	878	5,052	1%	0%	0%	0%	4%	5%
	Walk	1.4	0.0	18.4	4.5	400	547	0%	-	0%	0%	4%	4%
	Cycle	2.5	0.0	25.5	5.8	169	419	0%	-	0%	0%	4%	5%
	Metro/rail	11.0	715.8	61.1	10.8	49	536	-31%	164%	-13%	-21%	-72%	-80%
Business	*All*	*17.9*	*772.7*	*47.1*	*22.8*	*342*	*6,121*	*-2%*	*8%*	*-3%*	*1%*	*0%*	*-2%*
	Car	20.9	918.3	49.0	25.6	260	5,452	0%	0%	0%	0%	5%	5%
	Bus	6.3	100.6	44.2	8.6	32	200	1%	0%	1%	1%	4%	5%
	Walk	1.6	0.0	20.7	4.5	25	39	0%	-	0%	0%	3%	3%
	Cycle	2.8	0.0	27.5	6.2	7	20	1%	-	0%	0%	3%	4%
	Metro/rail	22.5	1214.8	67.8	19.9	18	409	-10%	147%	-10%	0%	-45%	-50%
Other	*All*	*9.3*	*226.8*	*39.3*	*14.3*	*14,202*	*132,755*	*-7%*	*8%*	*-6%*	*-1%*	*0%*	*-8%*
	Car	14.4	371.6	43.7	19.8	6,767	97,336	5%	5%	1%	4%	11%	16%
	Bus	6.3	100.6	43.1	8.7	3,847	24,057	1%	0%	0%	0%	6%	7%
	Walk	1.7	0.0	21.7	4.6	2,505	4,153	0%	-	0%	0%	5%	5%
	Cycle	2.6	0.0	26.3	6.0	702	1,839	1%	-	1%	0%	6%	7%
	Metro/rail	14.1	838.2	62.0	13.7	381	5,370	-36%	170%	-18%	-22%	-73%	-83%
All	*All*	*9.0*	*273.1*	*39.5*	*13.6*	*28,413*	*254,995*	*-5%*	*17%*	*-6%*	*1%*	*0%*	*-5%*
	Car	12.5	431.0	42.5	17.7	14,482	181,265	11%	12%	2%	8%	12%	24%
	Bus	6.7	100.7	44.2	9.1	7,488	50,056	9%	0%	3%	6%	7%	16%
	Walk	1.5	0.0	20.4	4.5	4,174	6,465	1%	-	0%	0%	4%	5%
	Cycle	2.6	0.0	26.2	6.0	1,402	3,660	2%	-	1%	1%	5%	6%
	Metro/rail	15.7	881.9	63.4	14.8	866	13,550	-31%	185%	-17%	-16%	-72%	-81%

The road and rail traffic comparison maps (**Figure 5.19** and **Figure 5.20**) show results that are in line with the discussions above.

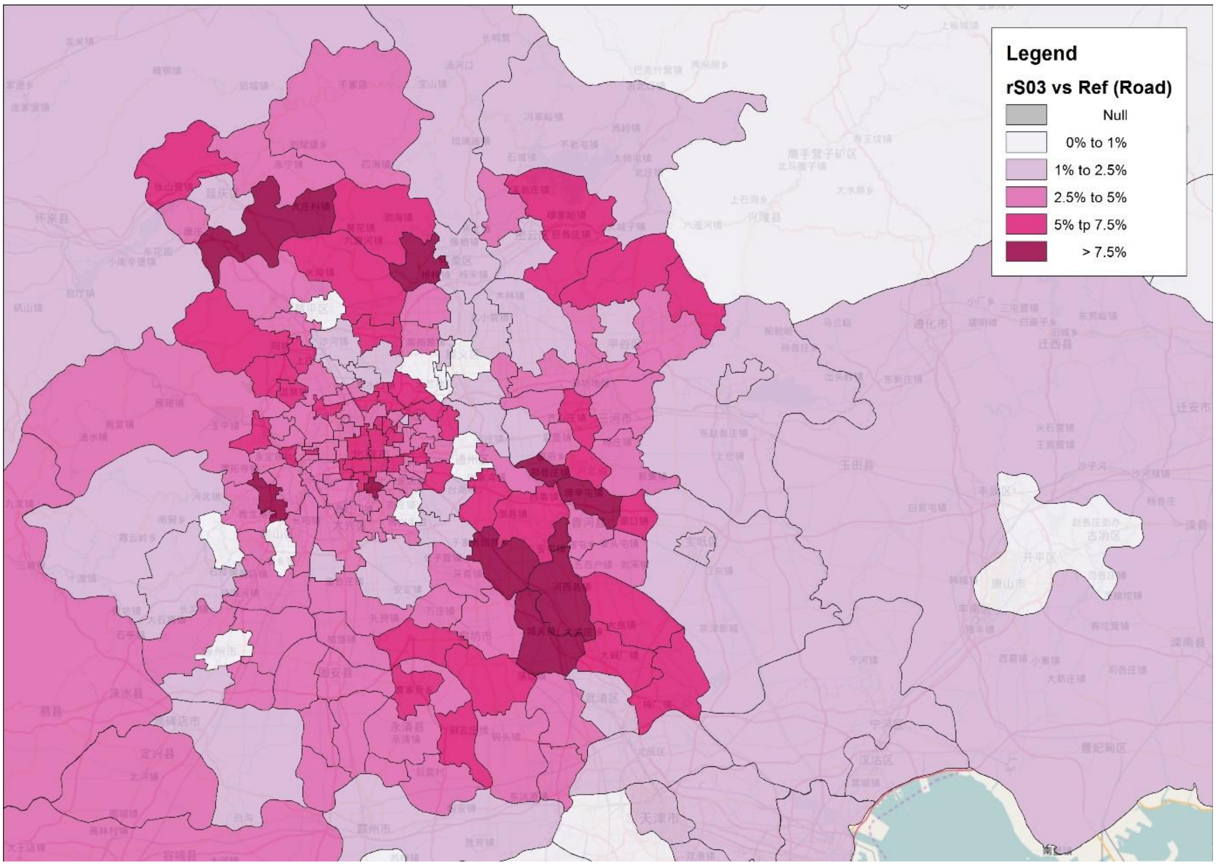


FIGURE 5.19. Road traffic comparison: rS03 vs Reference Case

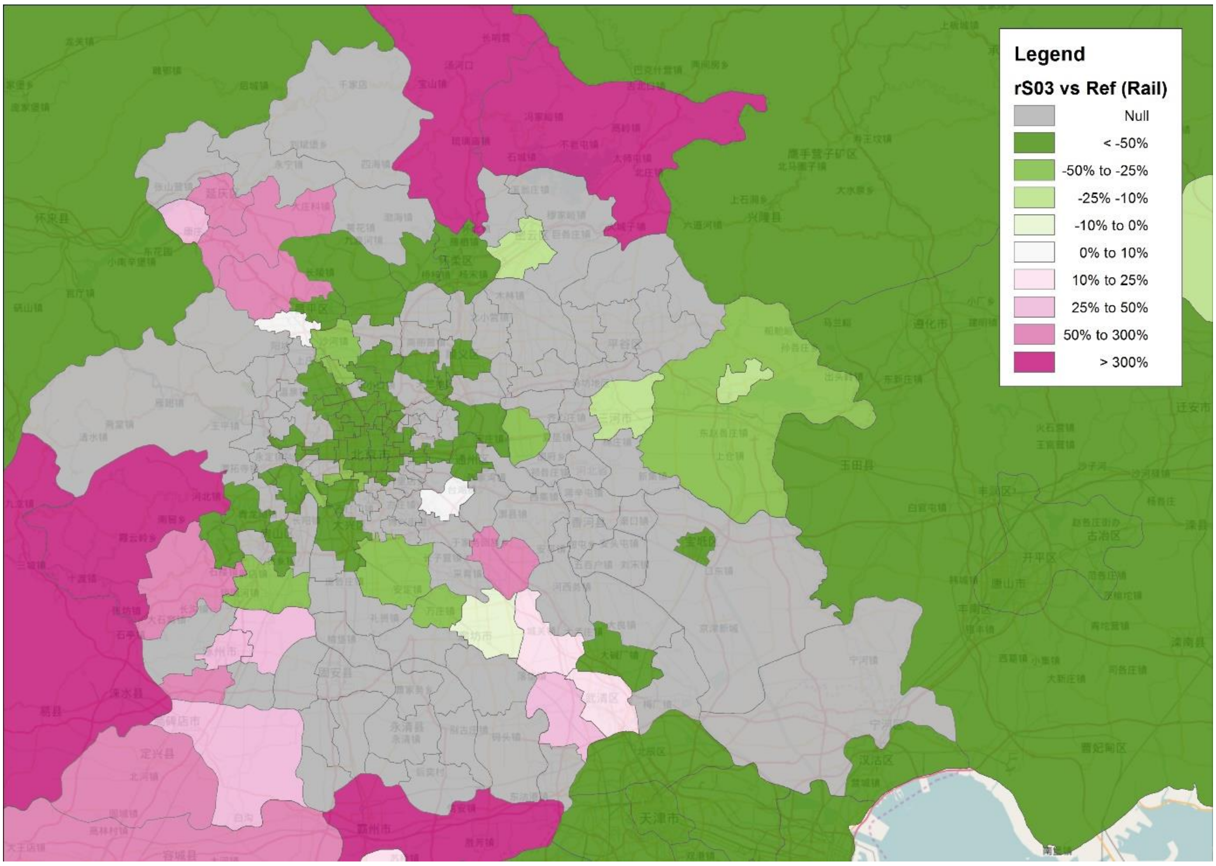


Figure 5.20. Rail traffic comparison: rS03 vs Reference Case

5.4.5. Test 10 – rS04

The limited spatial scope of the central Beijing districts coupled with the fixed land use means that the **rS04** results are very similar to those of S04. We therefore include the summary tables (**Table 5.16** and **Appendix 6 - Table A6.4**) and the road and rail comparison maps (**Figure 5.21** and **Figure 5.22**) for information only.

Table 5.16. Summary by trip purpose and mode: rS04 vs Reference Case

Scenario tests								Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	All	9.3	256.7	43.5	12.8	11,264	104,845	0%	-4%	1%	-1%	0%	0%
	Car	9.4	420.0	41.4	13.6	5,048	47,444	2%	1%	3%	-1%	-9%	-7%
	Bus	6.1	100.6	42.7	8.5	2,744	16,656	-1%	0%	0%	-1%	9%	7%
	Walk	1.4	0.0	18.5	4.5	1,310	1,816	1%	-	1%	0%	8%	8%
	Cycle	2.6	0.0	26.0	5.9	552	1,422	0%	-	0%	0%	9%	9%
	Metro/rail	23.3	307.9	77.9	17.9	1,610	37,508	-2%	0%	-1%	-1%	8%	6%
School	All	5.7	158.7	37.8	9.0	2,605	14,793	0%	-3%	0%	-1%	0%	0%
	Car	6.1	283.0	38.7	9.5	978	6,001	1%	1%	1%	0%	-7%	-5%
	Bus	5.7	100.6	41.4	8.2	877	4,982	-1%	0%	0%	0%	4%	4%
	Walk	1.4	0.0	18.4	4.5	401	549	0%	-	0%	0%	4%	4%
	Cycle	2.5	0.0	25.5	5.8	169	420	0%	-	0%	0%	5%	5%
	Metro/rail	15.8	269.9	70.2	13.5	180	2,841	-1%	-1%	0%	-1%	5%	4%
Business	All	18.2	707.8	50.5	21.6	342	6,217	0%	-1%	4%	-4%	0%	0%
	Car	21.4	933.1	52.0	24.7	237	5,077	3%	2%	6%	-3%	-4%	-2%
	Bus	6.1	100.6	43.5	8.4	35	211	-2%	0%	-1%	-1%	13%	11%
	Walk	1.6	0.0	20.8	4.5	27	42	1%	-	1%	0%	11%	12%
	Cycle	2.8	0.0	27.3	6.1	8	21	0%	-	0%	0%	12%	12%
	Metro/rail	24.4	481.6	74.4	19.6	36	866	-2%	-2%	-1%	-2%	8%	5%
Other	All	10.0	204.6	42.3	14.3	14,226	142,934	0%	-2%	1%	-1%	0%	-1%
	Car	14.1	362.7	44.1	19.2	5,654	79,932	3%	2%	2%	1%	-7%	-5%
	Bus	6.2	100.6	42.8	8.6	3,831	23,566	-1%	0%	0%	-1%	5%	5%
	Walk	1.7	0.0	21.7	4.6	2,500	4,153	0%	-	0%	0%	5%	5%
	Cycle	2.6	0.0	26.2	6.0	701	1,825	0%	-	0%	0%	5%	6%
	Metro/rail	21.7	308.0	74.9	17.4	1,539	33,458	-2%	-1%	-1%	-1%	7%	5%
All	All	9.5	227.1	42.5	13.4	28,437	268,789	0%	-3%	1%	-1%	0%	0%
	Car	11.6	391.8	42.7	16.3	11,918	138,454	3%	2%	2%	0%	-8%	-5%
	Bus	6.1	100.6	42.6	8.5	7,487	45,415	-1%	0%	0%	-1%	7%	5%
	Walk	1.5	0.0	20.4	4.5	4,238	6,559	0%	-	0%	0%	6%	6%
	Cycle	2.6	0.0	26.1	5.9	1,430	3,689	0%	-	0%	0%	7%	7%
	Metro/rail	22.2	307.7	76.1	17.5	3,365	74,672	-2%	-1%	-1%	-1%	7%	6%

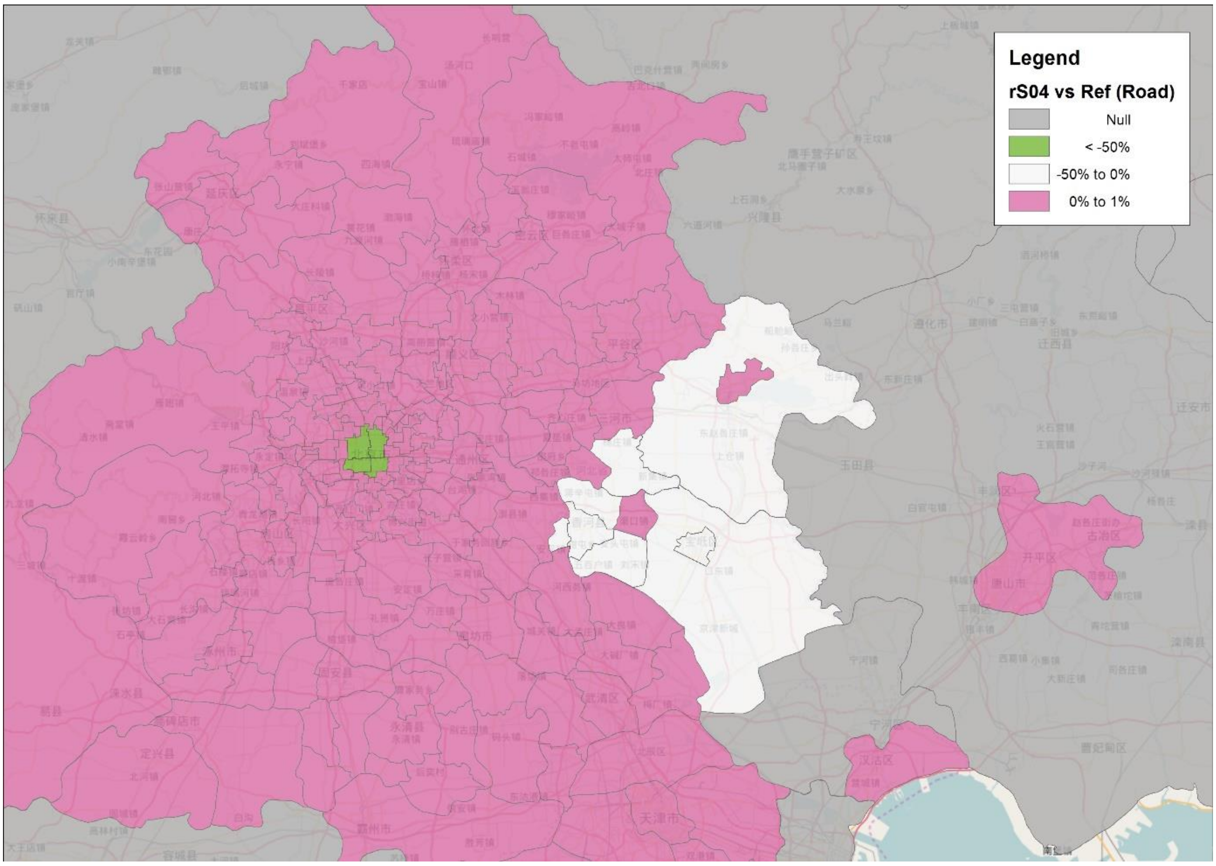


Figure 5.21. Road traffic comparison: rS04 vs Reference Case

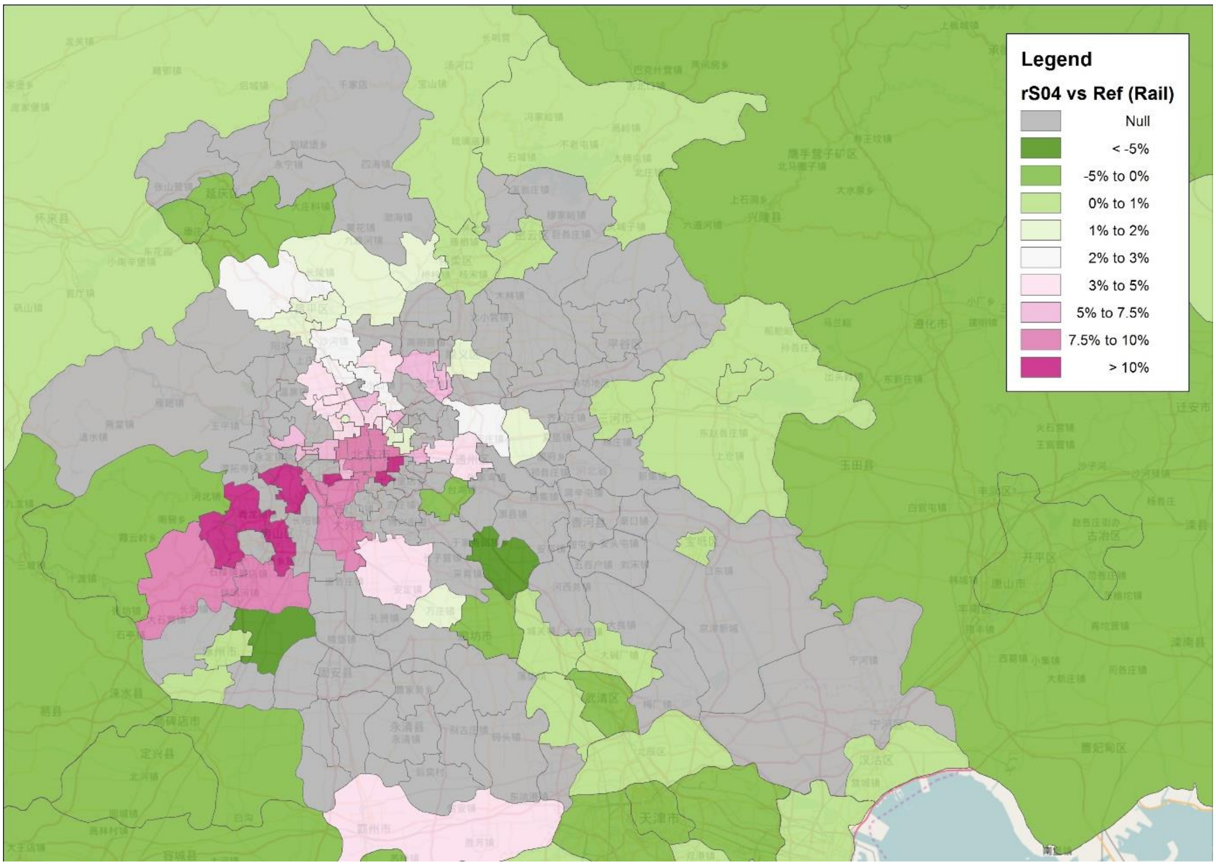


Figure 5.22. Rail traffic comparison: rS04 vs Reference Case

5.4.6. Test 11 – rS05

Table 5.17 summarise the modal spit results for **rS05**. rS05 similarly highlights the need to improve the access/egress and boarding/alighting times to/from bus services. As expected, rS05 does not alter the overall trip volume, but decreases the total trip-km by 1%. There is an even more sharp increase in bus patronage (by 94%) and bus trip-km (by 95%). The impacts are felt almost equally by all income groups (**Appendix 6 - Table A6.5**). Naturally, all non-bus modes lose mode share, but metro/rail loses the least (by 19%), followed by car (32%). The results suggest that redistribution would reinforce the impacts of modal shift. It would also slightly reduce the shift away from walking and cycling. The road and rail traffic comparison maps (**Figure 5.23** and **Figure 5.24**) support the analysis above.

Table 5.17. Summary by trip purpose and mode: rS05 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	*All*	*9.4*	*241.4*	*39.7*	*14.3*	*11,264*	*106,271*	*1%*	*-10%*	*-8%*	*10%*	*0%*	*1%*
	Car	10.8	479.1	41.0	15.8	3,774	40,649	17%	15%	2%	15%	-32%	-20%
	Bus	6.3	100.6	33.0	11.5	5,088	32,091	2%	0%	-23%	33%	102%	107%
	Walk	1.3	0.0	18.0	4.5	806	1,080	-3%	-	-2%	0%	-34%	-36%
	Cycle	2.6	0.0	26.0	5.9	323	829	0%	-	0%	0%	-36%	-36%
	Metro/rail	24.8	313.9	79.4	18.8	1,273	31,622	5%	2%	1%	4%	-15%	-11%
School	*All*	*5.8*	*142.9*	*33.0*	*10.5*	*2,604*	*15,053*	*2%*	*-12%*	*-12%*	*16%*	*0%*	*2%*
	Car	6.6	299.5	38.0	10.4	618	4,061	8%	7%	0%	9%	-41%	-36%
	Bus	5.5	100.6	30.9	10.7	1,529	8,424	-4%	0%	-26%	29%	82%	75%
	Walk	1.3	0.0	17.7	4.4	242	317	-4%	-	-3%	-1%	-37%	-40%
	Cycle	2.4	0.0	25.2	5.8	96	233	-2%	-	-1%	-1%	-40%	-42%
	Metro/rail	17.0	280.3	70.8	14.4	118	2,019	6%	3%	0%	6%	-31%	-26%
Business	*All*	*17.9*	*685.0*	*46.8*	*23.0*	*342*	*6,131*	*-2%*	*-5%*	*-4%*	*2%*	*0%*	*-2%*
	Car	22.4	975.3	50.0	26.9	217	4,874	7%	7%	2%	5%	-12%	-6%
	Bus	6.3	100.6	33.4	11.4	68	433	2%	0%	-24%	34%	123%	127%
	Walk	1.6	0.0	20.6	4.5	20	32	0%	-	0%	0%	-16%	-16%
	Cycle	2.8	0.0	27.6	6.2	6	16	2%	-	1%	1%	-16%	-14%
	Metro/rail	25.6	505.7	75.4	20.4	30	776	2%	3%	1%	2%	-8%	-6%
Other	*All*	*9.7*	*192.9*	*38.0*	*15.4*	*14,209*	*138,425*	*-4%*	*-8%*	*-9%*	*7%*	*0%*	*-4%*
	Car	15.8	402.8	44.1	21.4	4,179	65,905	15%	14%	2%	13%	-32%	-21%
	Bus	6.2	100.6	32.6	11.3	6,950	42,889	0%	0%	-24%	31%	91%	90%
	Walk	1.6	0.0	21.0	4.6	1,534	2,448	-3%	-	-3%	0%	-36%	-38%
	Cycle	2.6	0.0	26.0	5.9	415	1,067	-1%	-	0%	0%	-38%	-38%
	Metro/rail	23.1	317.1	76.0	18.2	1,131	26,117	4%	2%	1%	3%	-21%	-18%
All	*All*	*9.4*	*213.5*	*38.3*	*14.6*	*28,420*	*265,879*	*-1%*	*-9%*	*-9%*	*8%*	*0%*	*-1%*
	Car	13.1	442.5	42.5	18.5	8,788	115,488	16%	15%	2%	14%	-32%	-21%
	Bus	6.1	100.6	32.6	11.3	13,636	83,836	0%	0%	-24%	32%	94%	95%
	Walk	1.5	0.0	19.8	4.5	2,602	3,877	-3%	-	-3%	0%	-35%	-37%
	Cycle	2.6	0.0	25.9	5.9	841	2,144	-1%	-	0%	0%	-37%	-38%
	Metro/rail	23.7	316.0	77.5	18.4	2,553	60,533	5%	2%	1%	4%	-19%	-14%

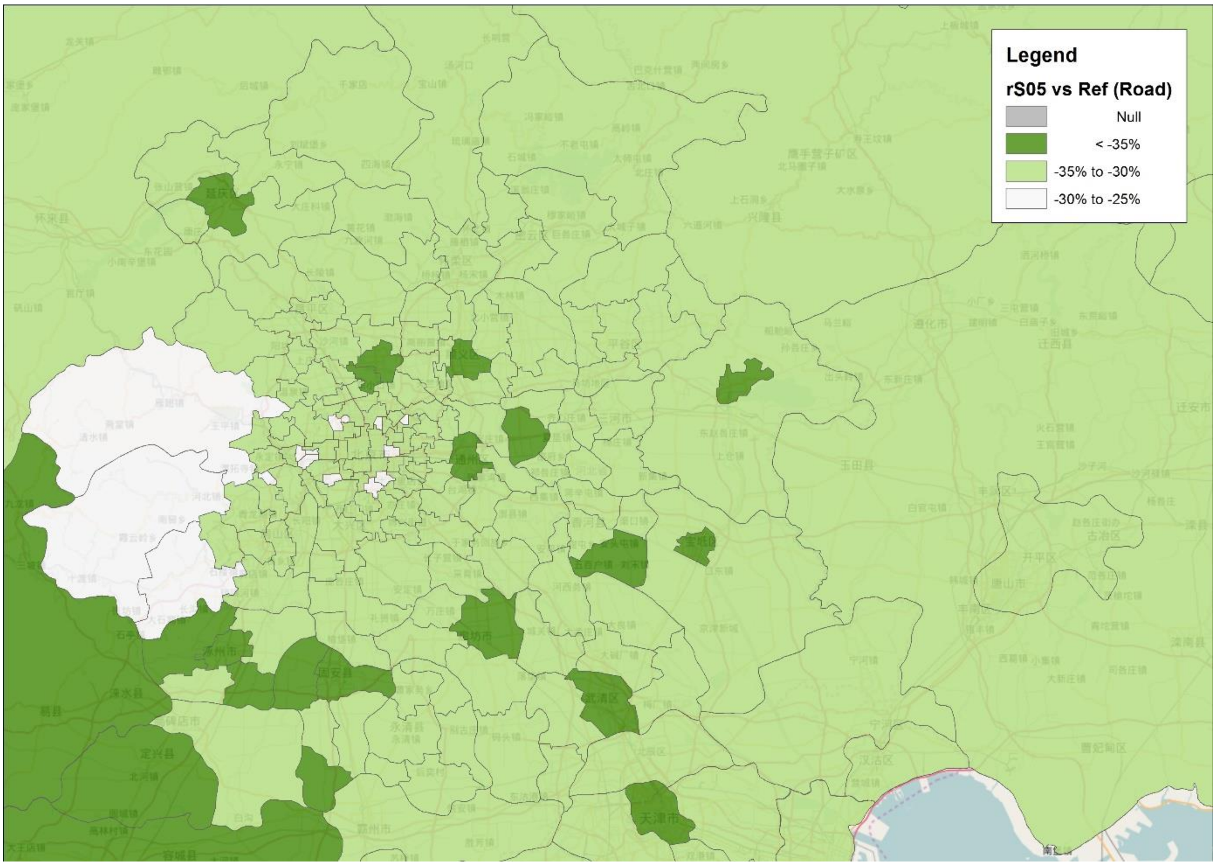


Figure 5.23. Road traffic comparison: rS05 vs Reference Case

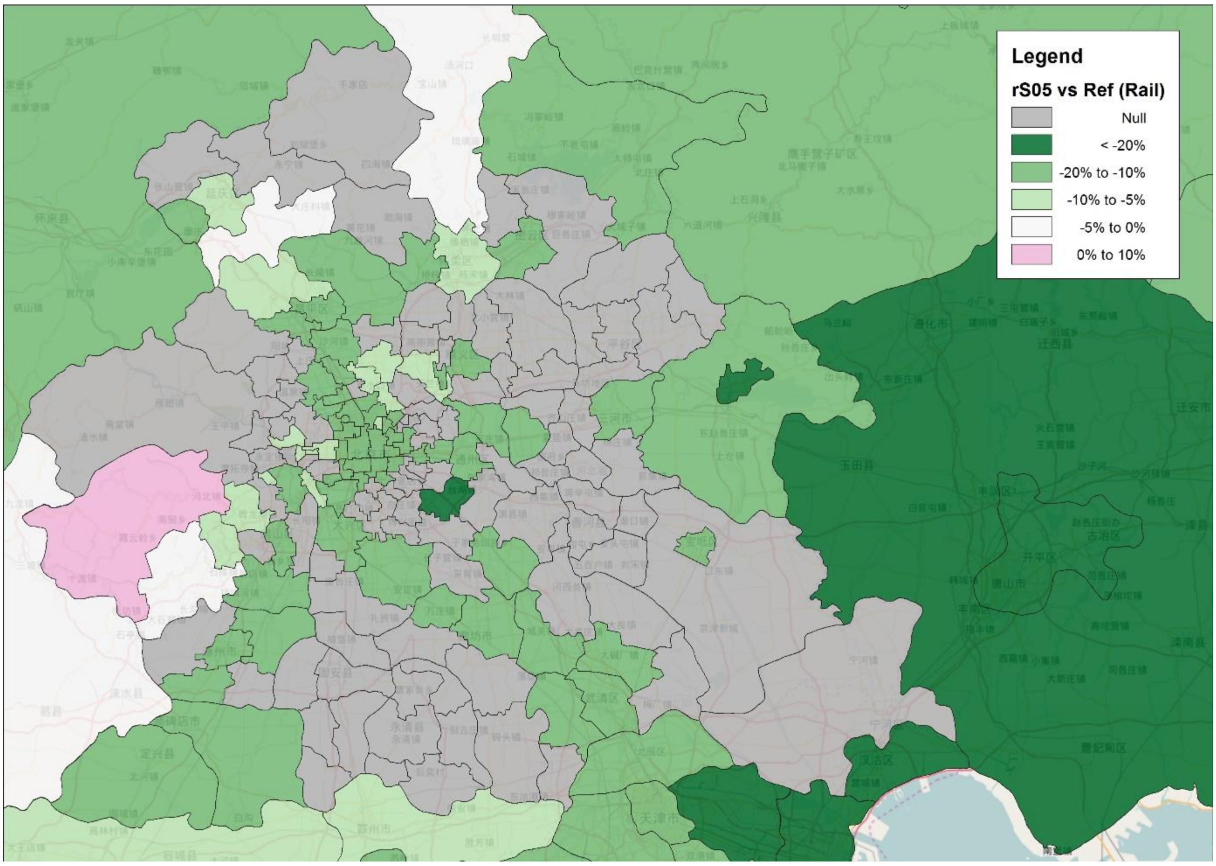


Figure 5.24. Rail traffic comparison: rS05 vs Reference Case

5.4.7. Test 12 – rS06

Results from **rS06** are not so different from those under S03 (**Table 5.18**). The significate increases in bus trip volume (by 82%) and trip-km (by 79%) are very similar to those of S06 (by 83% and by 79% respectively). However, metro/rail gains considerably more trip volume (by 45% vs 40% under S03) and trip-km (by 35% vs 30% under S03). The impacts are felt almost equally by all income groups for bus, although for metro the impacts are larger for the higher income groups (**Appendix 6 - Table A6.6**). Naturally, all non-bus/metro modes lose mode share, and this exacerbate the loss of mode share for walking and cycling to a significant extent. The road and rail traffic comparison maps (**Figure 5.25** and **Figure 5.26**) support the analysis above.

Table 5.18. Summary by trip purpose and mode: rS06 vs Reference Case

Scenario tests								Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
Work	***All***	***9.5***	***222.5***	***39.4***	***14.5***	***11,264***	***107,375***	***2%***	***-17%***	***-8%***	***12%***	***0%***	***2%***
	Car	9.8	435.2	40.3	14.5	3,334	32,530	6%	5%	0%	6%	-40%	-36%
	Bus	6.0	100.6	32.2	11.2	4,790	28,759	-2%	0%	-25%	30%	90%	85%
	Walk	1.3	0.0	17.8	4.5	777	1,029	-4%	-	-3%	-1%	-36%	-39%
	Cycle	2.5	0.0	25.6	5.9	308	771	-3%	-	-1%	-1%	-39%	-41%
	Metro/rail	21.5	279.3	64.7	20.0	2,055	44,287	-9%	-9%	-17%	10%	37%	25%
School	***All***	***6.2***	***145.6***	***33.8***	***11.0***	***2,606***	***16,063***	***8%***	***-11%***	***-10%***	***21%***	***0%***	***8%***
	Car	6.4	292.1	38.0	10.1	577	3,689	5%	4%	0%	6%	-45%	-42%
	Bus	5.5	100.6	30.9	10.7	1,450	7,982	-4%	0%	-26%	29%	73%	66%
	Walk	1.3	0.0	17.6	4.4	231	301	-4%	-	-4%	-1%	-40%	-43%
	Cycle	2.4	0.0	25.1	5.7	91	219	-3%	-	-2%	-1%	-44%	-45%
	Metro/rail	15.1	253.4	58.3	15.6	256	3,872	-5%	-7%	-17%	14%	50%	42%
Business	***All***	***18.2***	***663.2***	***46.9***	***23.2***	***342***	***6,212***	***0%***	***-8%***	***-4%***	***3%***	***0%***	***-1%***
	Car	22.7	985.9	50.2	27.1	203	4,619	9%	8%	3%	6%	-18%	-11%
	Bus	6.3	100.6	33.2	11.4	64	405	1%	0%	-24%	34%	110%	112%
	Walk	1.5	0.0	20.4	4.5	19	30	-1%	-	-1%	0%	-20%	-21%
	Cycle	2.8	0.0	27.4	6.1	5	15	0%	-	0%	0%	-21%	-20%
	Metro/rail	22.9	401.1	63.2	21.7	50	1,143	-9%	-18%	-16%	9%	52%	39%
Other	***All***	***10.3***	***192.7***	***38.8***	***15.9***	***14,229***	***146,613***	***2%***	***-8%***	***-7%***	***10%***	***0%***	***2%***
	Car	15.4	393.8	44.0	21.1	3,727	57,544	13%	11%	2%	11%	-39%	-31%
	Bus	6.1	100.6	32.5	11.3	6,492	39,842	-1%	0%	-24%	31%	79%	77%
	Walk	1.6	0.0	20.9	4.6	1,443	2,289	-4%	-	-4%	-1%	-39%	-42%
	Cycle	2.5	0.0	25.8	5.9	387	980	-2%	-	-1%	-1%	-42%	-43%
	Metro/rail	21.1	284.6	63.2	20.0	2,180	45,958	-5%	-8%	-16%	14%	52%	45%
All	***All***	***9.7***	***205.8***	***38.7***	***15.1***	***28,441***	***276,263***	***2%***	***-12%***	***-8%***	***11%***	***0%***	***2%***
	Car	12.5	419.3	42.1	17.9	7,841	98,382	11%	9%	1%	10%	-39%	-33%
	Bus	6.0	100.6	32.2	11.2	12,797	76,988	-2%	0%	-25%	30%	82%	79%
	Walk	1.5	0.0	19.6	4.5	2,470	3,648	-4%	-	-4%	-1%	-38%	-41%
	Cycle	2.5	0.0	25.7	5.9	792	1,985	-3%	-	-1%	-1%	-41%	-42%
	Metro/rail	21.0	281.7	63.6	19.8	4,541	95,260	-7%	-9%	-17%	12%	45%	35%

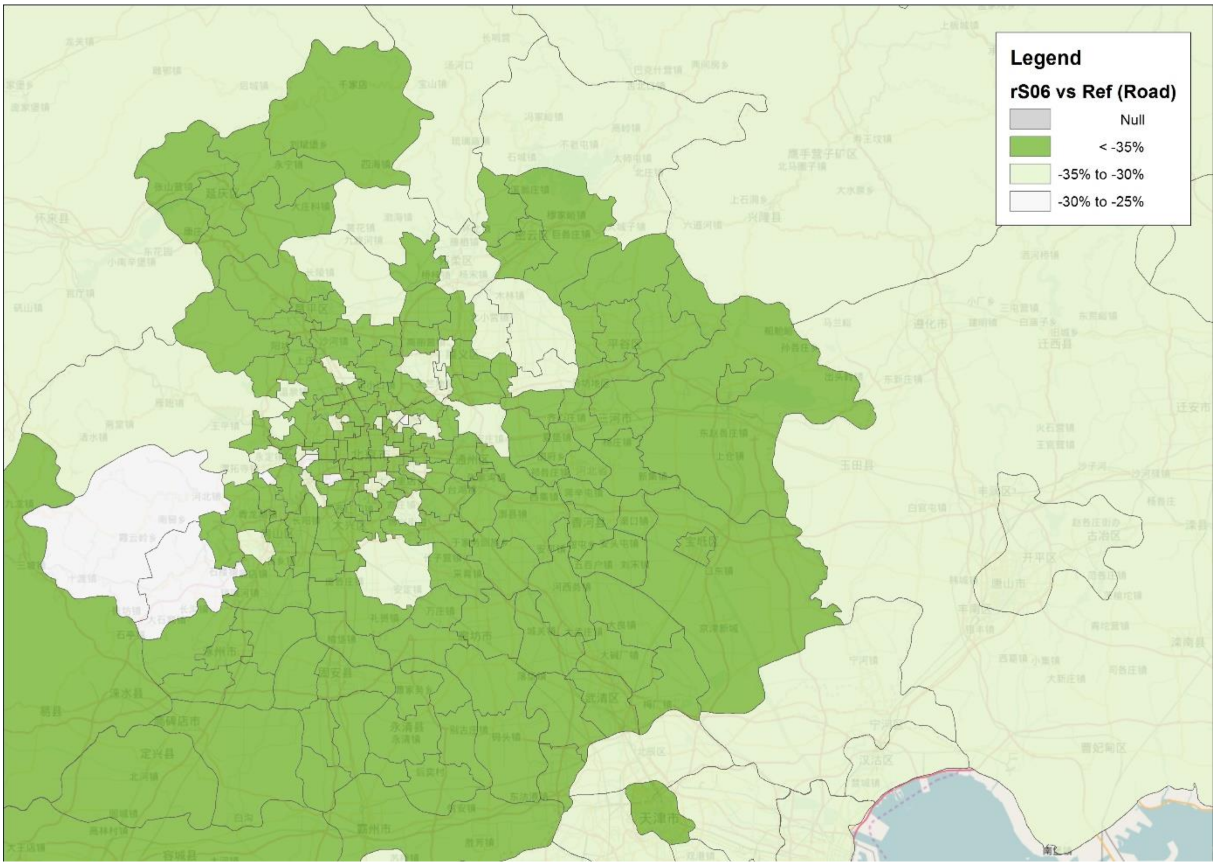


Figure 5.25. Road traffic comparison: rS06 vs Reference Case

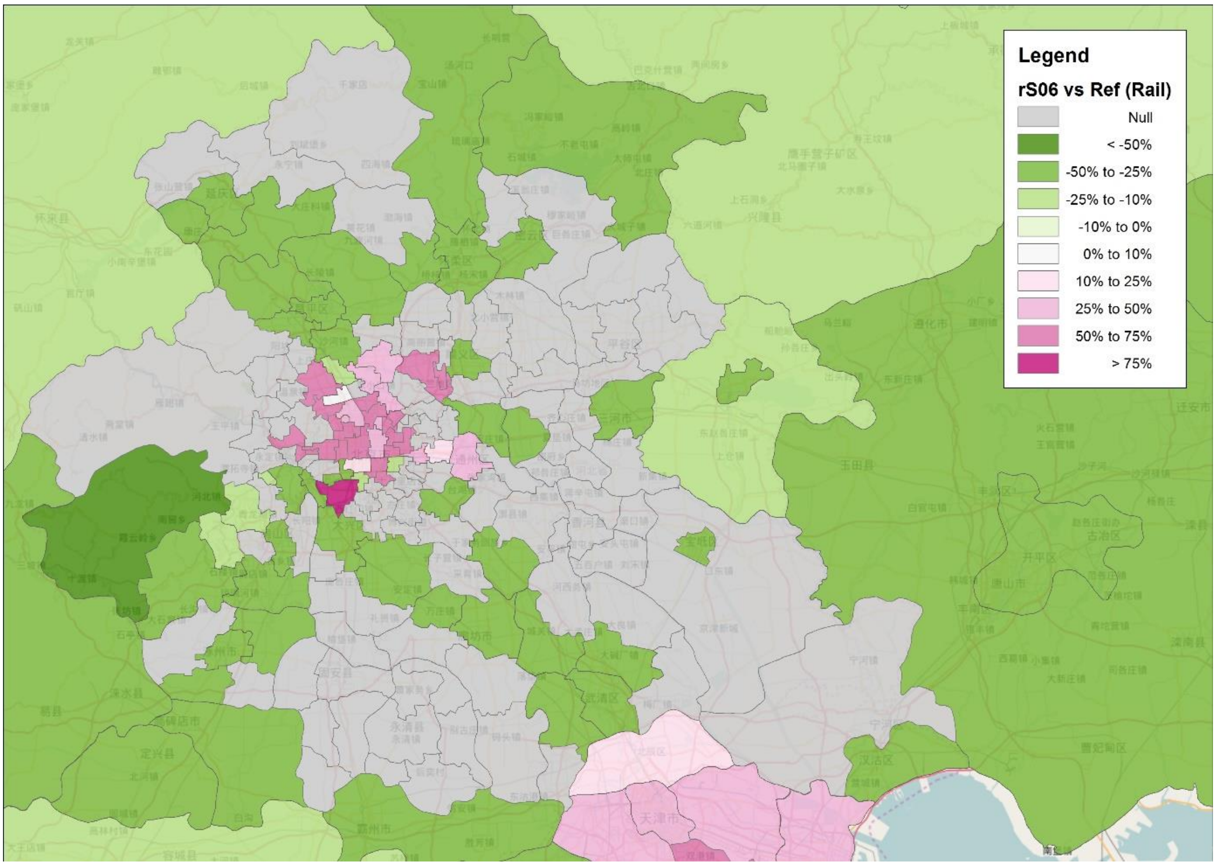


Figure 5.26. Rail traffic comparison: rS06 vs Reference Case

5.5. Assessment on road capacity extension

As shown in **Table 5.20**, our model predicts a significant surge in on-road traffic in Beijing between 2015 and 2030 (Reference Case). Within the Central Area, trip volumes (PCU) on the 1st city major road links and the 2nd ring road are predicted to increase by over 300% (310% and 377% respectively) in 2030 (Reference Case); traffic along the ring roads in the wider City Fringes are even expected to be more than quintuple in 2030 (Reference Case).

Such a mushrooming on-road traffic demand can lead to severe adverse impacts on both environment and economy, bringing stress to travellers and residents. There are potentially two ways to ease this imbalance of road traffic between demand and supply.

One way to is to enhance the level of supply by expanding road capacities. Based on the linear demand-supply (pcu-capacity) curve, it is required a further expansion of 1.6 billion urban road capacities (pcu per 3-hour morning peak) in Beijing by 2030 to meet the on-road traffic demand (**Table 5.19**). But in consideration of the worsening shortage in land and the growing cost of construction, this approach of mega-scale investment seems to be too costly to be implemented and too risky to yield any benefit.

Table 5.19. Estimated road capacity expansion in Beijing by 2030 (reference case)

Road Type	Trip Volume (pcu)		Capacity (pcu/morning peak)		
	2010	2030	2010	2030	Growth
Urban road	35,145,717	145,295,191	516,640,500	2,135,844,002	1,619,203,502
Expressway	5,719,949	25,679,032	44,586,000	200,163,544	155,577,544
Total (within Beijing)	***40,865,666***	***170,974,223***	***561,226,500***	***2,336,007,546***	***1,774,781,046***

Political intervention is another way to address the issue. Results of the scenario tests (please refer to **§5.3** for detailed definitions and assumptions of difference scenarios) show that:

(1) In the short-term, **S06** – enhanced metro and rail accessibility (i.e. shorter metro and rail access/egress time) turns to be the most effective way to suppress the road traffic within the Beijing Central Area (by 35% in comparison with the Reference Case);

(2) In the City Fringe areas, **S01** – road user charge seems to work best for the short term to curb the car traffic (by 25% in comparison with the Reference Case);

(3) For the long-term, **S01** is the best measure to inhibit road traffic for the entire Beijing, by 36% and 38% (versus Reference Case) respectively for the Central and Fringe areas.

(4) It is also worth noting that enhanced bus accessibility (**S05** – reduced bus access/egress time) has only small impact on reducing the road traffic demand (less than 6% and 12%

respectively for short term and long term), and concessionary bus travel (**S02** – free bus tickets) is unlikely to affect the car trip demand very much (with only minuscule overall difference of -1% to -2%). Meanwhile, increase in metro ticket price (**S03**), even only by 0.5 Yuan per km, can shot the car trip volumes up, especially in the Central Area (by 59% in the short term and 39% in the long term).

Table 5.20. Comparison of on-road traffic in Beijing: 2010 Base Year, 2030 Reference Case, Short-term and Long-term scenarios

Link Type	Trip Volume (PCU)		Percentage Difference												
	Base Year 2010	Ref. Case 2030	Base vs. Ref.	Ref. vs. Short-Term						Ref vs. Medium-Term					
				S01	S02	S03	S04	S05	S06	rS01	rS02	rS03	rS04	rS05	rS06
Beijing - Central Area (Within 2nd Ring Road)															
1st-class urban major	1,192,650	4,884,594	310%	-37%	-1%	71%	-22%	-7%	-37%	-41%	-2%	47%	-25%	-12%	-36%
2nd-class urban major	691,927	2,730,615	295%	-29%	0%	70%	-17%	-7%	-35%	-35%	0%	49%	-20%	-11%	-34%
3nd-class urban major	1,439,073	5,621,695	291%	-33%	0%	62%	-18%	-6%	-35%	-38%	-1%	42%	-21%	-11%	-34%
4th-class urban major	138,040	516,092	274%	-25%	2%	53%	-17%	-7%	-38%	-27%	2%	45%	-19%	-10%	-38%
Ring road	883,921	4,215,744	377%	-21%	3%	36%	-8%	-7%	-34%	-30%	2%	19%	-10%	-13%	-34%
Subtotal	***4,345,610***	***17,968,741***	***313%***	***-30%***	***0%***	***59%***	***-16%***	***-7%***	***-35%***	***-36%***	***-1%***	***39%***	***-19%***	***-12%***	***-34%***
Beijing - City Fringe (Between 2nd and 6th Ring Road)															
1st-class urban major	4,549,294	17,755,199	290%	-25%	0%	33%	-5%	-6%	-25%	-36%	-2%	23%	-6%	-12%	-27%
2nd-class urban major	6,976,028	28,079,714	303%	-24%	-1%	28%	-2%	-6%	-21%	-37%	-2%	22%	-2%	-12%	-25%
3nd-class urban major	9,425,849	34,083,644	262%	-22%	-1%	27%	-3%	-6%	-22%	-33%	-2%	20%	-3%	-12%	-24%
4th-class urban major	1,554,995	5,660,021	264%	-20%	-1%	23%	-2%	-7%	-21%	-32%	-2%	17%	-3%	-12%	-23%
Ring road	8,293,941	41,747,872	403%	-28%	-1%	21%	-1%	-5%	-19%	-46%	-3%	14%	0%	-13%	-23%
Subtotal	***30,800,106***	***127,326,450***	***313%***	***-25%***	***-1%***	***26%***	***-2%***	***-6%***	***-21%***	***-38%***	***-2%***	***19%***	***-2%***	***-12%***	***-24%***
Beijing – Total (Within 6th Ring Road)															
1st-class urban major	5,741,944	22,639,793	294%	-27%	0%	41%	-9%	-6%	-27%	-37%	-2%	28%	-10%	-12%	-29%
2nd-class urban major	7,667,954	30,810,329	302%	-24%	-1%	31%	-3%	-6%	-23%	-36%	-2%	24%	-3%	-12%	-26%
3nd-class urban major	10,864,922	39,705,340	265%	-24%	-1%	32%	-5%	-6%	-24%	-34%	-2%	23%	-5%	-12%	-25%
4th-class urban major	1,693,035	6,176,113	265%	-20%	-1%	26%	-4%	-7%	-22%	-32%	-2%	19%	-4%	-12%	-24%
Ring road	9,177,862	45,963,616	401%	-28%	0%	22%	-1%	-5%	-20%	-44%	-2%	14%	-1%	-13%	-24%
Subtotal	***35,145,717***	***145,295,191***	***313%***	***-25%***	***-1%***	***30%***	***-4%***	***-6%***	***-23%***	***-38%***	***-2%***	***21%***	***-4%***	***-12%***	***-25%***

5.6. Summary

Figure 5.27 to **Figure 5.30** summarise the discussions above by presenting the distance frequency distributions for car trips and all trips as predicted by the strategic transport model for 2010, 2030 reference case, and twelve alternative scenario tests (i.e. S01-S06 and rS01-rS06). A comparison of the profiles for 2030 vs those of 2010 indicates that there are significantly large travel demand changes which cannot be adequately analysed through marginal transport improvement scenarios. Instead, broad visions of the evolution of travel demand in the Greater Beijing region are necessary in considering effective measures in managing the potential surge in traffic levels. Although car tolling can be an effective demand management measure, its impact on the overall levels of demand reduction does not appear to be as large as bold improvements in bus access/egress and boarding/alighting times. If the road network could be managed in such a way that (e.g. through a careful conversion of road space for car to that dedicated for the non-car modes) as buses become faster, the road speeds are kept constant (such as at the 2008-2010 levels), the overall demand for road space could be reduced by up to 30% compared with 2030 reference case. A reduction in bus fares or an increase in metro fares is unlikely to affect the road space demand in significant ways by themselves. Controlling car access to and from the central Beijing districts can achieve a remarkable effect in reducing car traffic, although the impacts are limited to the local area.

More generally, the model tests highlight the dominating impacts upon the rise in travel demand through economic growth, income effects and lifestyle changes. They also show that the distribution of land use activities has a critical influence on travel and the choice of travel modes. Furthermore, improving bus transport (and to some extent metro and light rail) could inadvertently divert passengers away from walking and cycling. This suggests that land use and urban design both at the strategic scale (i.e. for activity distribution) and at the micro scale (e.g. to enable passengers walk and cycle to public transport stops/stations in shorter time and cleaner air) could have a win-win effect. We will turn to the discussions of the implications of the findings, and the strengths and weaknesses of the model in **Chapter 6**.

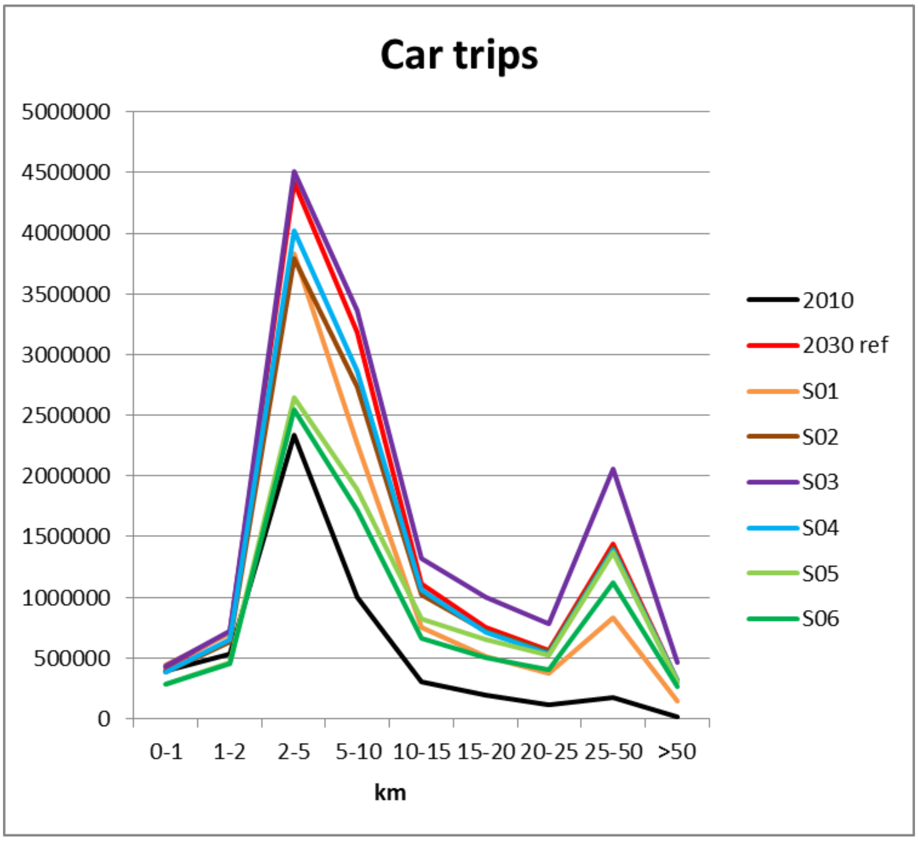


Figure 5.27. Comparison of the trip frequency distribution profiles
<Car trips for 2010, 2030 reference case and tests S01-S06>

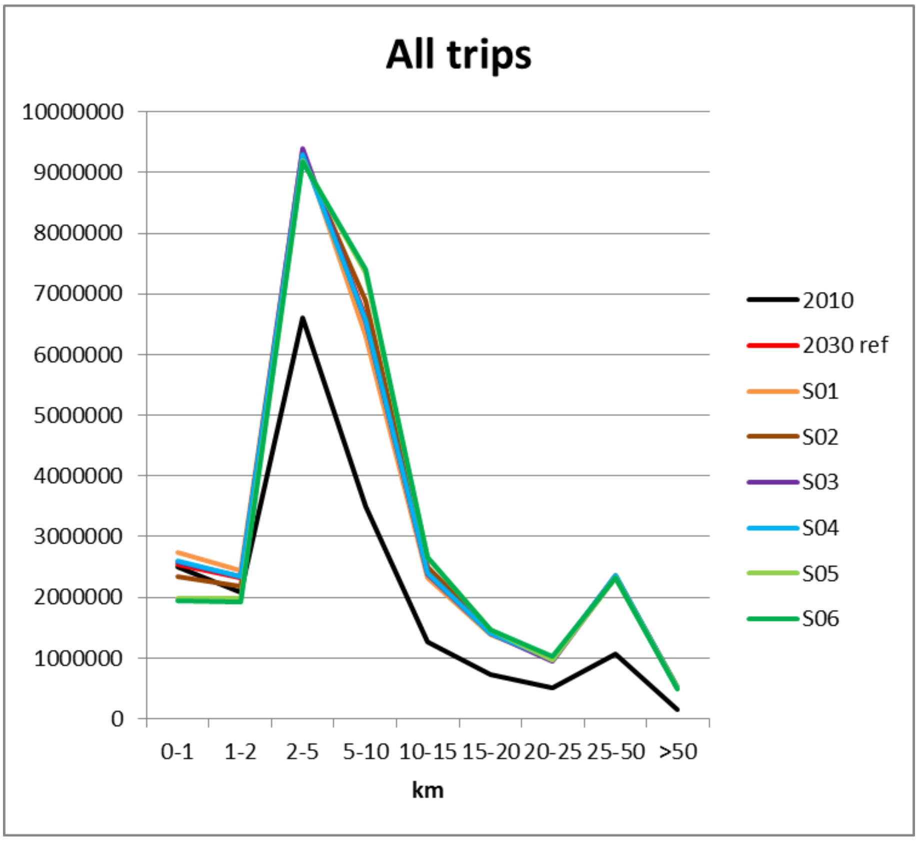


Figure 5.28. Comparison of the trip frequency distribution profiles
<All trips (including walking and cycling) for 2010, 2030 reference case and tests S01-S06>

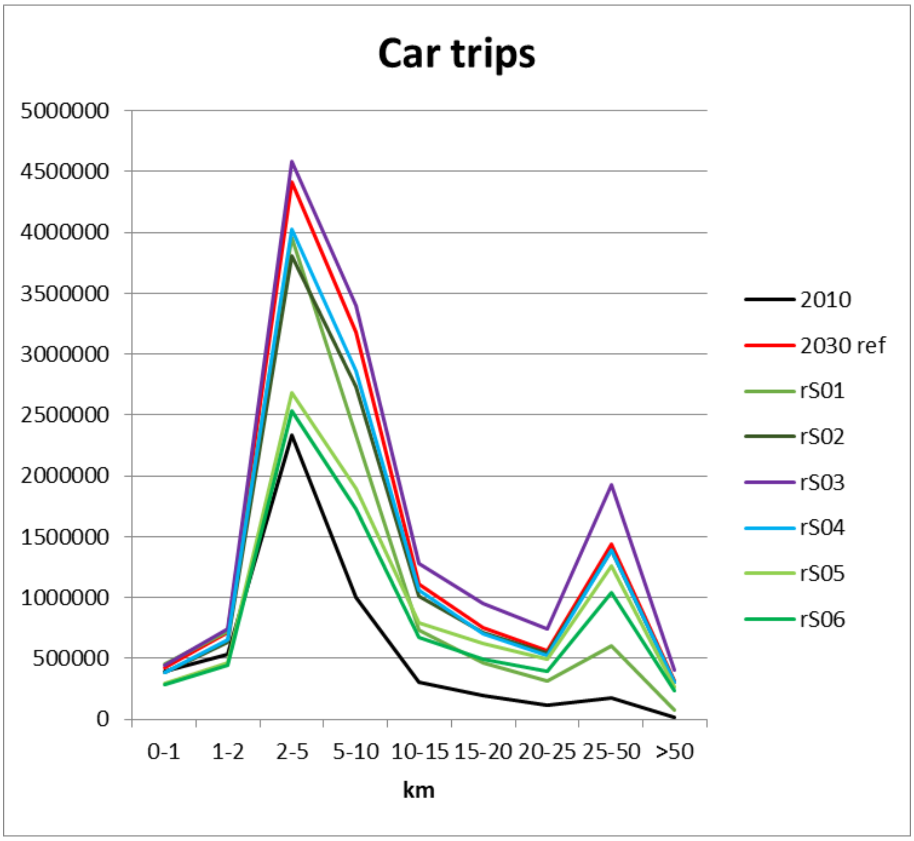


Figure 5.29. Comparison of the trip frequency distribution profiles
<Car trips for 2010, 2030 reference case and tests rS01-rS06>

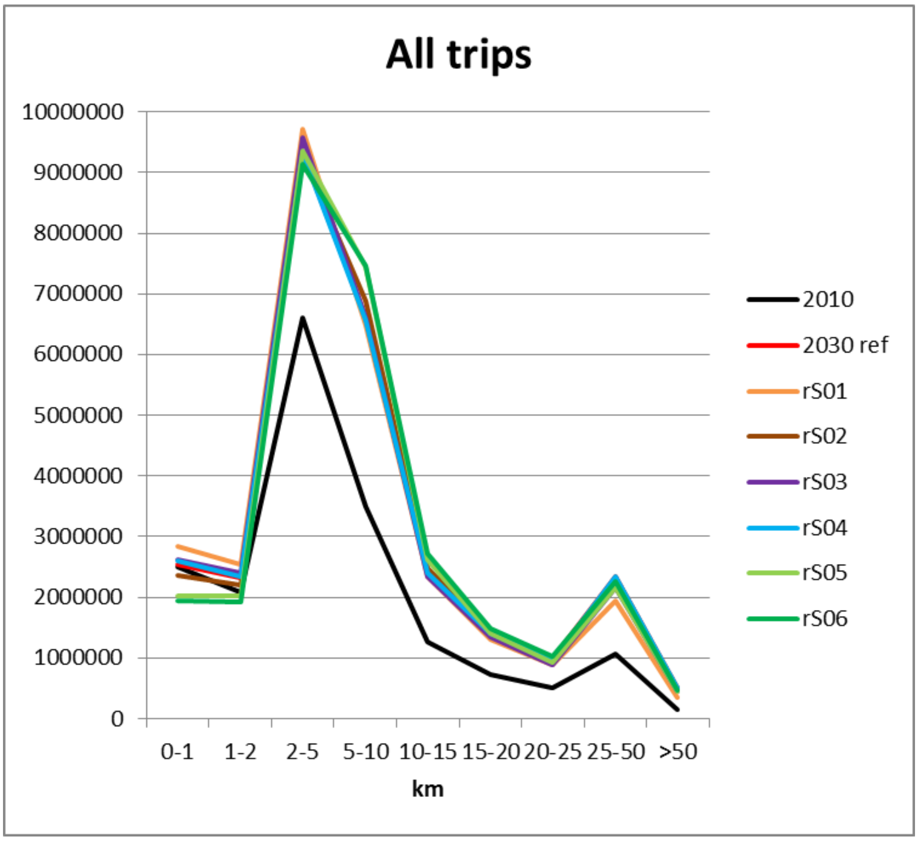


Figure 5.30. Comparison of the trip frequency distribution profiles
<All trips (including walking and cycling) for 2010, 2030 reference case and tests rS01-rS06>

6. Conclusion

The main hypothesis of this dissertation is that an incorporation of the micro-level smart data and analyses in strategic urban transport modelling will make it feasible to establish a sufficiently robust strategic transport model for evidence-based policy analysis with cost, time, and skill thresholds that are close to being affordable in developing country cities. In this dissertation we have tested this hypothesis through carrying out a number of novel model development tasks.

In particular, we have developed new modelling tools that use medium-level quality GPS taxi traces to identify slow-moving and stopping traffic hotspots using an extended density-based spatial clustering algorithm that is tolerant of significant data noise, and building on the insights of the data analysis, further to estimate congested road speeds (which used to be very costly and time-consuming to obtain if at all before the GPS traces become available). The micro-level network, congested speeds, and insights into the nature of the congested traffic have been incorporated into a MEPLAN-based strategic transport model interacting with a MEPLAN-based land use and travel demand model. This model system further benefits from theoretically robust predictions of job and residential locations in the city region for 2030. This means that the strategic economic, social and environmental impacts of transport interventions can be tested in a robust way through accounting for the interactions among transport, land-use and background social-technical trends. We hope that the work presented in this dissertation has built the foundations for a new approach to establish and test the medium to long term visions for alternative travel demand management and transport investment scenarios.

The methods and algorithms have been tested in a case study of the Greater Beijing region. The results suggest that the new approach developed in this dissertation has made it not only cheaper and faster to develop a robust model, but could also potentially fill a gap in the lack of medium to long term perspectives regarding major road and metro investments over the next two decades. Such analyses could be of critical importance in improving the performance of the transport system in terms of safety, economic efficiency, air quality, and carbon reduction given the long lead times to plan and deliver transport infrastructure investments.

In other words, the research work carried out in this dissertation has augmented the contents of strategic transport modelling in situations where travel demand growth is characterised by non-marginal scenarios. Such situations are common in growing cities in fast urbanising countries.

In this concluding chapter we first discuss the findings and insights in the model development process and the model scenario tests. We then consider the strengths and weaknesses of the model system, and further developments that will be beneficial for academic and policy research.

6.1. Findings and insights

In the order of the research work presented in this dissertation, we summarise the findings from the analyses of the taxi GPS traces, the calibration and validation of the strategic transport model, the predictions for the 2030 reference case which represents a continuation of current measures with no significant changes, and the tests of the alternative scenarios.

The analyses of the taxi GPS traces and the estimation of congested road speeds for February 2008 show that such new data sources are a welcome new input which can be used to address previously long-standing and costly procedures such as understanding traffic operation patterns and obtaining congested road speeds at the city scale. The unprecedented, wide coverage of the road links in a large metropolitan area is great news for monitoring patterns of congestion. Overall, the validation exercise for the congested speeds suggests that our proposed method is capable of providing a satisfactory estimation of the road link speeds across a network the size of Beijing. These congested link speeds produce estimated travel times for a randomly generated sample of trips that are within acceptable levels when compared with observed travel times. This is especially true when the trips are generated using time intervals of no longer than 60 seconds. However, the validation exercise shows that there is a considerable margin of error in the estimation (only 50% of the 1626 estimations having errors smaller than 37%). Notwithstanding the fact that those errors are inherent with such datasets with low or inconsistent-precision of individual observations, and the comparison of a mean speed with individual observations, there is room to improve the quality of the data collected as well as to make an effort for more of the GPS traces to be available for research and modelling.

The overall performance of the strategic transport model for Base Year 2010 would seem in general satisfactory. Both the interzonal and intrazonal networks that have been introduced to the model are working as intended, with the congested road speeds playing a key part in rapid model calibration. The model has been used successfully in conjunction with the land use and travel demand model to represent well the observed patterns of trip volumes by trip purpose, distance frequency distribution and mode shares in aggregate for the main built-up area in Beijing, although it is yet to be tested in greater geographical detail in this area and in areas outside Beijing when observed data becomes available. Model validation is currently performed in terms of travel demand elasticity tests with respect to modal costs and travel times. The elasticity ranges for both 2010 and 2030 are very different from the international benchmark range such as available in the UK. Nevertheless they appear sensible for the current income levels and fare structures in Beijing: the car fuel price elasticities are higher than the UK range because the residents have much lower income levels even in 2030 than in the UK today; the public transport fare elasticities are relatively low in the model, which results from the fact that the fares are kept very low (the fares in 2010 are 1 yuan flat for bus journeys and 2 yuan flat for metro) and they are a very small component of the generalised travel costs.

The 2030 reference scenario is a rather unique one which has made use of the estimated February 2008 congested road link speeds (i.e. same as used in the 2010 model calibration) – this implies a scenario where Beijing manages to achieve reasonable road speeds through a combination of road investments, metro line expansions and other associated transport improvements. This is based on the assumption that under ordinary circumstances, a city will tackle traffic congestion and adapt in some way to massive gridlocks. The patterns of jobs and resident household locations are predicted in RSE-Beijing, an external spatial economic and land use activity model using the same assumption. The 2030 reference case results suggest that if the road congestion conditions remain the same as in 2010 without demand management measures, the morning peak passenger trip volume is likely to rise by 54.3%, and trip-km by 99.2% overall. Car traffic in particular will rise by 154.7% and car trip-km by 369.2%. As the trend development pattern has relatively poor land use/transport coordination (such as today), the significant further expansion of the metro network would only attract a very modest level of trip volume and trip-km (38.3% and 30.9% respectively). For commuting, overall the metro passenger volume would only rise by 5.5% and trip-km 0.4%, as the more diffused jobs and residential locations coupled with a strong shift to higher income, car owning households make car travel a better choice in the newly expanded suburban areas. Buses on the whole have managed to hold on to its mode share, whilst walk and particularly cycling suffer an overall decline in mode share. This confirms our expectation that the foreseen transformations of the economy, demography and lifestyles are the dominant influences upon travel demand, and this non-marginal change will have profound impacts on the urban transport systems. In particular, the public transport modes can potentially be facing a serious challenge. Car travel demand will rise greatly for all income groups if the road speeds are kept at the 2010 network conditions without further demand management measures, and the requirements for road space would be impossible to deliver.

The approach of using acceptable road speeds in medium to long term forecasting scenarios does not imply predict-and-provide. This is because we are able to test alternative transport scenarios on the model that implement a variety of demand management measures. The twelve alternative scenario tests (i.e. S01-S06 which represent short term travel responses, and rS01-rS06 which represent medium term responses with trip redistribution effects but no overall changes in job and household locations). Although car tolling can be an effective demand management measure, its impact on the overall levels of demand reduction does not appear to be as large as bold improvements in radically reducing bus access/egress and boarding/alighting times. If the road network could be managed in such a way that (e.g. through a careful conversion of road space for car to that dedicated for the non-car modes) as buses become faster, the road speeds are kept constant (such as at the 2008-2010 levels), the overall demand for road space could be reduced by up to 30% compared with 2030 reference case. A reduction in bus fares or an increase in metro fares is unlikely to affect the road space demand in significant ways by themselves. Controlling car access to and from the central Beijing districts can achieve a remarkable effect in reducing car traffic, although the impacts are limited to the local area. In all of the scenarios however, there appear to be a large rise in the demand for road space, especially in the area between the third and the sixth ring road in Beijing.

The 2030 reference case and alternative scenario tests highlight the dominating impacts upon the rise in travel demand through economic growth, income effects, and lifestyle changes. They also show that the distribution of land use activities has a critical influence on travel and the choice of travel modes. Furthermore, improving bus transport (and to some extent metro and light rail) could inadvertently divert passengers away from walking and cycling. This suggests that land use and urban design both at the strategic scale (i.e. for activity distribution) and at the micro scale (e.g. to enable passengers walk and cycle to public transport stops/stations in shorter time and cleaner air) could have a win-win effect. The alternative scenarios can be further refined to analyse transport network designs that optimise such effects.

The model design does provide the possibility to feed back the changed transport costs and generalised costs to RSE-Beijing, the spatial economic and land use activity model which will in turn forecast changes in job and household locations. In fact, this interactive process of running the two models together could help refining both transport and land use scenario design. In the scenario tests alternative patterns of acceptable road travel times (i.e. other than the estimated February 2008 road link times) may be used, including solving the congested road travel times through iterating between the strategic transport model and RSE-Beijing. This dissertation has established a framework for doing so but it is beyond the scope of the dissertation to carry out such tests.

6.2. Strengths, weaknesses and further development of the model

The integrative structure of the strategic transport model designed in this dissertation is an ambitious one. It not only covers all modes of passenger travel in a very large city region, but also account for a variety of land use responses. Its usage in the wide-ranging scenario tests has highlighted its strengths, weaknesses, and the needs for further development, especially those relating to strategic issues (e.g. impacts of road tolling, land use/transport interaction, etc.) that other transport models are less well placed to address.

The model design is comprehensive in its potential to address a wide range of policy initiatives. Its key strength lies in the wide range of behavioural responses that it represents. It represents the changes in matrices of trips and in average trip lengths at a level of segmentation of households that can be supported by existing data sources. It can also potentially represent the changes in the locations of households, either within its land use and travel demand module or through interfacing with RSE-Beijing, the external spatial economic and land use activity model. This can be seen as a unique strength of this strategic model that complement well other, shorter term operational traffic forecasting models that may be in use in city regions of this size.

The framework of the strategic transport model can also be used to accumulate sporadic transport surveys and other data collection initiatives in the Greater Beijing region, so that the evidence base can be enhanced.

To achieve a comprehensive urban activity and modal coverage while retaining computational feasibility, the model sacrifices some spatial detail through the design of relatively large model zones and so only has a more limited ability to test small scale local network improvements with precision. In this manner it is complementary to spatially detailed assignment models. The granularity of spatial representation can be improved through either an increase in the number of model zones for the study area or an implementation of adaptive zoning (see Hagen-Zanker and Jin, 2013; 2012) in the future.

The least satisfactory aspects of the model results are the road link loadings. This is because the relatively large zones imply a significant proportion of traffic is modelled on intrazonal links. Although the model results cover comprehensively the mode choice behaviour across all travel, currently the road link level forecasts for particular neighbourhoods are difficult to use. There have been methods developed to convert intrazonal traffic onto interzonal road links (such as in Echenique et al, 1994), but such methods a contingent on specific road network configurations and are resource intensive. There is scope to improve the model through a finer zoning map or an application of adaptive zoning as above, which can be implemented using standard methods already available.

On rail, metro and light rail networks, the current model makes use of average link transit times rather than timetabled transit services. The MEPLAN implementation of the model provides the option to upgrade the coding using transit lines, which may be helpful for modelling e.g. complex metro service operations in the future (The current peak time service patterns are fairly simple and straightforward with few branching or trunking services).

The personal trips for purposes other than commuting and employer's business are currently modelled in a relatively simple way. No differentiation has been made with respect to different shopping journeys, or different leisure journeys, in terms of trip attractions. BTRC (2012) shows that such non-commuting personal trips are short and local for the peak periods. However, for inter-peak modelling, such trips are important components of trip making, so that it would be beneficial in the future to improve the trip attraction and distribution models for those trip purposes. The model design has left place holders for the time periods other than the morning peak, and more detailed categorisation of the trip purposes. There is also a scope to include the light and heavy goods vehicles in the model, which are respectively important for the inter-peak and night times.

When the detailed transport survey data becomes available, it would be helpful to model household car ownership levels explicitly. This is because as the cities become denser and public transport improves, the higher income households may choose to forego or reduce car ownership. This is observed to take place in the dense urban areas of the developed country cities. When this happens, household socio-economic profiles or income levels will cease to be a good indicator of their car ownership levels. Modelling explicitly household car ownership will therefore avoid overestimating the car ownership and car traffic levels of the higher income households in dense urban areas.

It is clear that there are many gaps in the current statistics and surveys, which hold back what can be achieved in model design, calibration and validation. We hope that new smart data sources from traffic and urban activity monitoring and administrative records of land use and transport projects will emerge in the near future so that they will contribute to the improvement of this strategic transport model. In the case of planning and administrative data sources, an important restriction data confidentiality, which is an essential consideration similar to data privacy issues. A useful approach to overcoming data confidentiality issues is to collaborate with the government agencies in model development, which cannot be easily done for a PhD dissertation, but it is hoped that the strategic transport model for Beijing has been developed to an adequate extent in this dissertation to enable such collaboration to take place in the next steps.

Appendix 1 Model Zone Definition

Table A1.1 in this appendix define the zone numbers for each traffic zone. Zonal maps (**Figure A1.1 - Figure A1.4**) present the location of each zone.

Table A1.1. Definition of zone numbers

Zone	District	Zone	District	Zone	District	Zone	District	Zone	District
1	XiCheng	50	ChaoYang	98	ChangPing	159	Other	217	Other
2	DongCheng	51	ChaoYang	99	ChangPing	161	Other	219	Other
3	ChongWen	52	ChaoYang	100	ShunYi	162	Other	250	Other
4	XuanWu	53	HaiDian	101	PingGu	163	Other	251	Other
10	Fengtai	54	ChaoYang	102	ShunYi	168	Other	256	Other
11	ChaoYang	55	HaiDian	103	ShunYi	170	Other	257	Other
12	Fengtai	56	HaiDian	104	ChangPing	171	Other	261	Other
13	Fengtai	57	ChaoYang	105	ShunYi	172	Other	262	Other
14	Fengtai	58	HaiDian	106	ShunYi	174	Other	269	Other
15	ChaoYang	59	ChaoYang	107	MenTouGou	175	Other	273	Other
16	Fengtai	60	HaiDian	108	ShunYi	176	Other	274	Other
17	Fengtai	61	HaiDian	109	ChangPing	177	Other	275	Other
18	Fengtai	62	ChaoYang	110	ChangPing	178	Other	282	Other
19	Fengtai	63	HaiDian	111	ChangPing	179	Other	284	Other
20	Fengtai	64	HaiDian	112	PingGu	180	Other	291	Other
21	Fengtai	65	HaiDian	113	PingGu	181	Other	292	Other
22	ChaoYang	70	DaXing	114	ShunYi	182	Other	298	Other
23	ChaoYang	71	DaXing	115	ShunYi	183	Other	299	Other
24	Fengtai	72	FangShan	116	ChangPing	184	Other	303	Other
25	Fengtai	73	DaXing	117	ChangPing	185	Other	304	Other
26	ChaoYang	74	DaXing	118	PingGu	186	Other	311	Other
27	ChaoYang	75	DaXing	119	ShunYi	187	Other	312	Other
28	ShiJingShan	76	FangShan	120	ShunYi	188	Other	315	Other
29	ShiJingShan	77	TongZhou	121	PingGu	189	Other	316	Other
30	ChaoYang	78	FangShan	122	ChangPing	191	Other	318	Other
31	ShiJingShan	79	FangShan	123	PingGu	192	Other	319	Other
32	ShiJingShan	80	DaXing	124	HuaiRou	193	Other	320	Other
33	ChaoYang	81	TongZhou	125	ChangPing	194	Other	321	Other
34	HaiDian	82	FangShan	126	HuaiRou	195	Other	322	Other
35	ChaoYang	83	DaXing	127	MiYun	196	Other	323	Other
36	HaiDian	84	FangShan	128	YanQing	197	Other	324	Other
37	ChaoYang	85	DaXing	129	HuaiRou	198	Other	331	ChaoYang
38	ChaoYang	86	DaXing	130	YanQing	199	Other	332	Other
39	ChaoYang	87	TongZhou	131	YanQing	201	Other	341	Other
40	ShiJingShan	88	FangShan	132	MiYun	202	Other	348	Other
41	HaiDian	89	TongZhou	133	MiYun	204	Other	351	Other
42	ChaoYang	90	TongZhou	134	YanQing	205	Other	352	Other
43	ChaoYang	91	MenTouGou	135	YanQing	206	Other	353	Other
44	HaiDian	92	TongZhou	136	YanQing	207	Other	361	Other
45	ChaoYang	93	FangShan	137	MiYun	208	Other	364	Other
46	HaiDian	94	TongZhou	138	HuaiRou	209	Other	370	Other
47	ShiJingShan	95	MenTouGou	150	Other	211	Other	371	Other
48	ChaoYang	96	TongZhou	152	Other	215	Other	372	Other
49	ChaoYang	97	ShunYi	156	Other	216	Other	373	Other
								374	Other

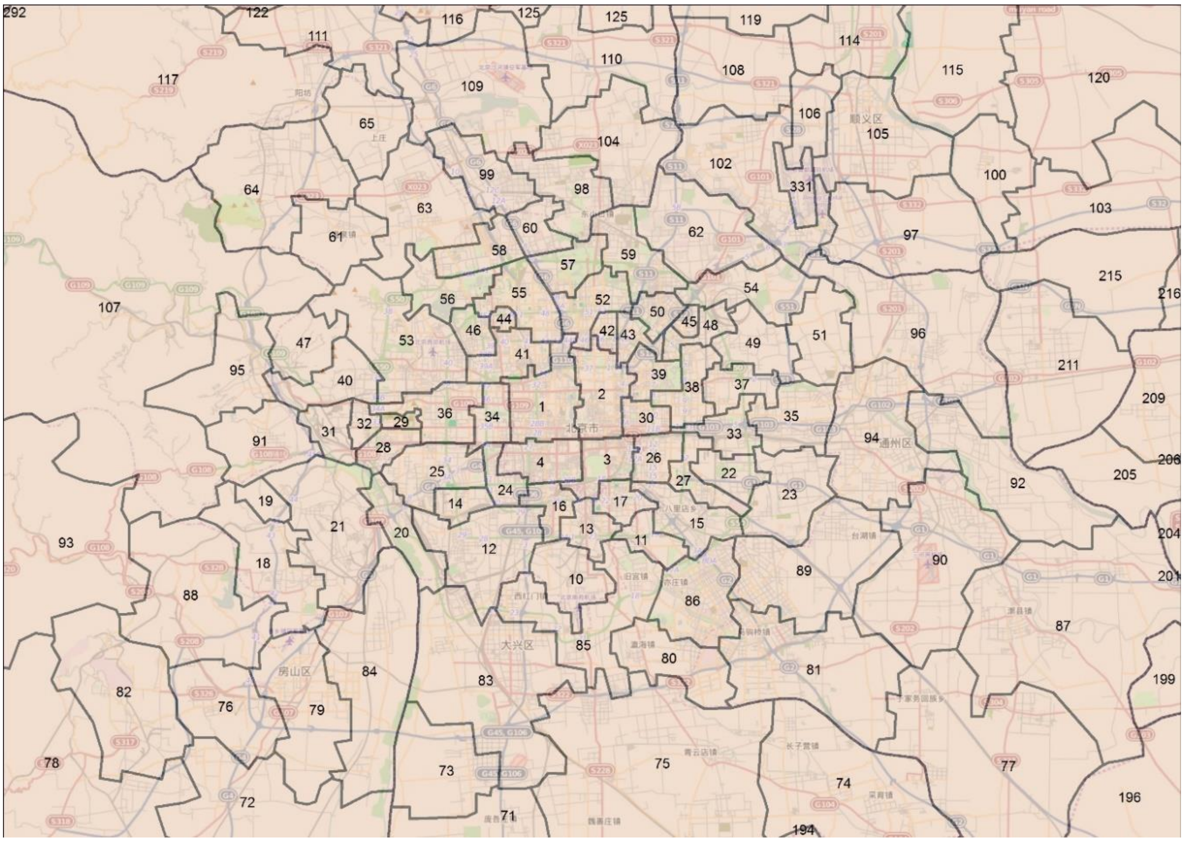


Figure A1.1. Model zones in Beijing

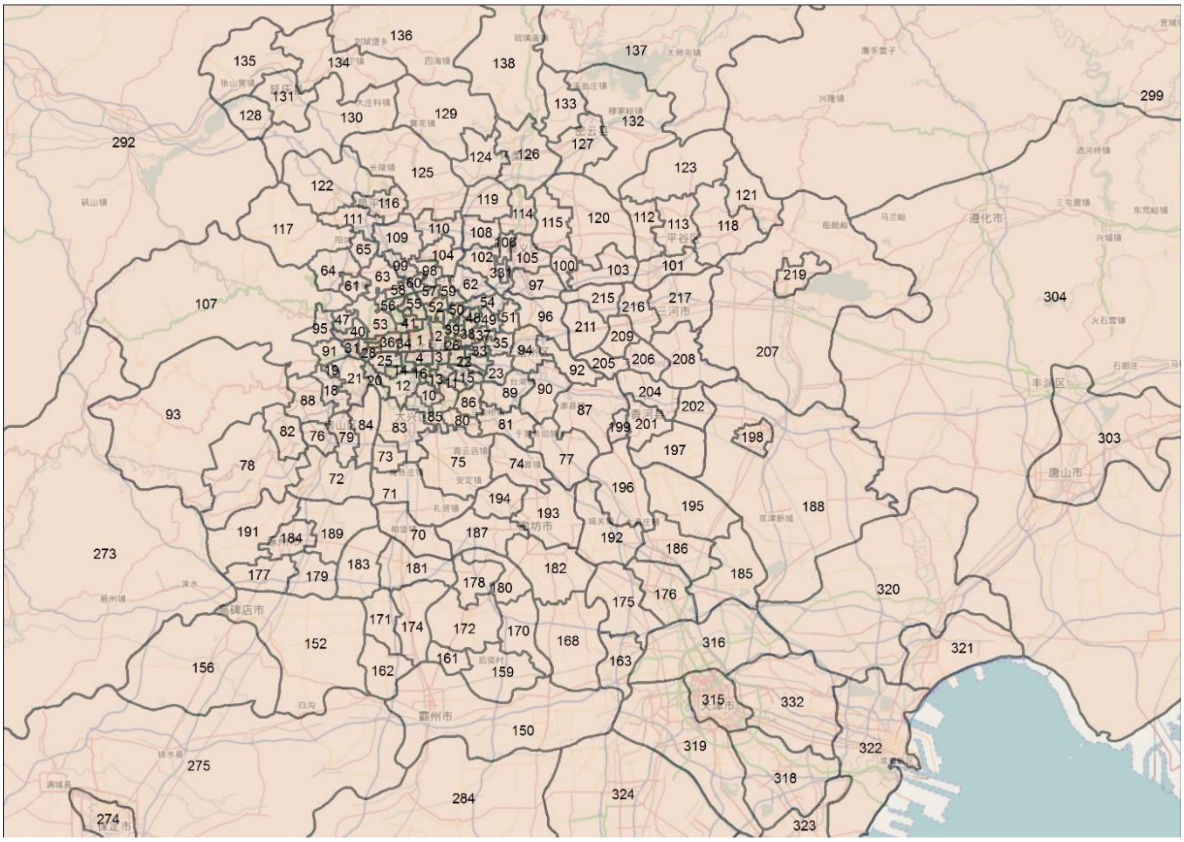


Figure A1.2. Model zones in Beijing and the Southeast Surrounding Region

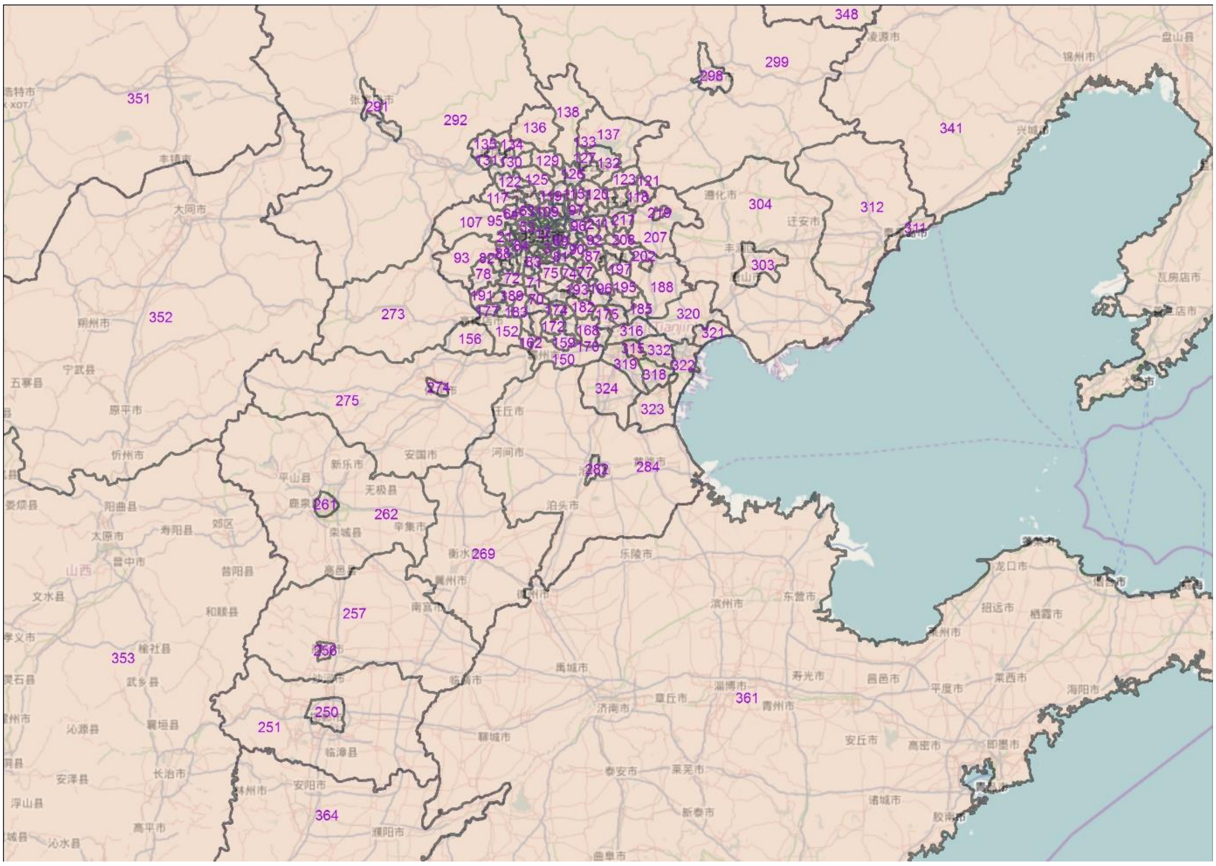


Figure A1.3. Model zones in Hebei Province

Figure A1.4. All model zones

Appendix 2 Network link types and modes definitions

The tables (**Table A2.1 – Table A2.6**) in this appendix define for each link type the network modes that can make use of them. Because there is a long list of link types, they are grouped in separate tables below.

Table A2.1. Intrazonal Link Types

Type	Type Name	Unit	Mode	Description	Type	Type Name	Unit	Mode	Description
4001	IntraRoad1	pcu/period	101	IntraCar	4015	IntraRoad15	pcu/period	105	IntraCar
4001	IntraRoad1	pcu/period	111	IntraBus	4015	IntraRoad15	pcu/period	115	IntraBus
4001	IntraRoad1	pcu/period	121	IntraWalk	4015	IntraRoad15	pcu/period	135	IntraCycle
4001	IntraRoad1	pcu/period	131	IntraCycle	4016	IntraRoad16	pcu/period	106	IntraCar
4002	IntraRoad2	pcu/period	102	IntraCar	4016	IntraRoad16	pcu/period	116	IntraBus
4002	IntraRoad2	pcu/period	112	IntraBus	4017	IntraRoad17	pcu/period	107	IntraCar
4002	IntraRoad2	pcu/period	122	IntraWalk	4017	IntraRoad17	pcu/period	117	IntraBus
4002	IntraRoad2	pcu/period	132	IntraCycle	4018	IntraRoad18	pcu/period	108	IntraCar
4003	IntraRoad3	pcu/period	103	IntraCar	4018	IntraRoad18	pcu/period	118	IntraBus
4003	IntraRoad3	pcu/period	113	IntraBus	4019	IntraRoad19	pcu/period	109	IntraCar
4003	IntraRoad3	pcu/period	123	IntraWalk	4019	IntraRoad19	pcu/period	119	IntraBus
4003	IntraRoad3	pcu/period	133	IntraCycle	4031	IntraRail31	pcu/period	141	IntraRail
4004	IntraRoad4	pcu/period	104	IntraCar	4032	IntraRail32	pcu/period	142	IntraRail
4004	IntraRoad4	pcu/period	114	IntraBus	4033	IntraRail33	pcu/period	143	IntraRail
4004	IntraRoad4	pcu/period	134	IntraCycle	4034	IntraRail34	pcu/period	144	IntraRail
4005	IntraRoad5	pcu/period	105	IntraCar	4035	IntraRail35	pcu/period	145	IntraRail
4005	IntraRoad5	pcu/period	115	IntraBus	4036	IntraRail36	pcu/period	146	IntraRail
4005	IntraRoad5	pcu/period	135	IntraCycle	4037	IntraRail37	pcu/period	147	IntraRail
4006	IntraRoad6	pcu/period	106	IntraCar	4038	IntraRail38	pcu/period	148	IntraRail
4006	IntraRoad6	pcu/period	116	IntraBus	4039	IntraRail39	pcu/period	149	IntraRail
4007	IntraRoad7	pcu/period	107	IntraCar	4051	IntraRail51	pcu/period	141	IntraRail
4007	IntraRoad7	pcu/period	117	IntraBus	4052	IntraRail52	pcu/period	142	IntraRail
4008	IntraRoad8	pcu/period	108	IntraCar	4053	IntraRail53	pcu/period	143	IntraRail
4008	IntraRoad8	pcu/period	118	IntraBus	4054	IntraRail54	pcu/period	144	IntraRail
4009	IntraRoad9	pcu/period	109	IntraCar	4055	IntraRail55	pcu/period	145	IntraRail
4009	IntraRoad9	pcu/period	119	IntraBus	4056	IntraRail56	pcu/period	146	IntraRail
4011	IntraRoad11	pcu/period	101	IntraCar	4057	IntraRail57	pcu/period	147	IntraRail
4011	IntraRoad11	pcu/period	111	IntraBus	4058	IntraRail58	pcu/period	148	IntraRail
4011	IntraRoad11	pcu/period	121	IntraWalk	4059	IntraRail59	pcu/period	149	IntraRail
4011	IntraRoad11	pcu/period	131	IntraCycle	4071	IntraRail71	pcu/period	141	IntraRail
4012	IntraRoad12	pcu/period	102	IntraCar	4072	IntraRail	pcu/period	142	IntraRail
4012	IntraRoad12	pcu/period	112	IntraBus	4073	IntraRail	pcu/period	143	IntraRail
4012	IntraRoad12	pcu/period	122	IntraWalk	4074	IntraRail	pcu/period	144	IntraRail
4012	IntraRoad12	pcu/period	132	IntraCycle	4075	IntraRail	pcu/period	145	IntraRail
4013	IntraRoad13	pcu/period	103	IntraCar	4076	IntraRail	pcu/period	146	IntraRail
4013	IntraRoad13	pcu/period	113	IntraBus	4077	IntraRail	pcu/period	147	IntraRail
4013	IntraRoad13	pcu/period	123	IntraWalk	4078	IntraRail	pcu/period	148	IntraRail
4013	IntraRoad13	pcu/period	133	IntraCycle	4079	IntraRail	pcu/period	149	IntraRail
4014	IntraRoad14	pcu/period	104	IntraCar	501	Intra road	pcu/period	10	Car
4014	IntraRoad14	pcu/period	114	IntraBus	501	Intra road	pcu/period	20	Bus
4014	IntraRoad14	pcu/period	134	IntraCycle	501	Intra road	pcu/period	30	Walk
					501	Intra road	pcu/period	40	Cycle

Table A2.2. Expressway Link Types

Type	Type Name	Unit	Mode	Mode Name	Description
1001	Expressway	pcu/period	10	Car	Jing Ha (G1)
1001	Expressway	pcu/period	20	Bus	
1001	Expressway	pcu/period	91	FeederCar	
1001	Expressway	pcu/period	92	FeederBus	
1001	Expressway	pcu/period	93	FeederWalk	
1001	Expressway	pcu/period	94	FeegerCycl	
1001	Expressway	pcu/period	95	FeederUnd	
1002	Expressway	pcu/period	10	Car	Jing Hu (G2)
1002	Expressway	pcu/period	20	Bus	
1002	Expressway	pcu/period	91	FeederCar	
1002	Expressway	pcu/period	92	FeederBus	
1002	Expressway	pcu/period	93	FeederWalk	
1002	Expressway	pcu/period	94	FeegerCycl	
1002	Expressway	pcu/period	95	FeederUnd	
1004	Expressway	pcu/period	10	Car	Jing Shi (G4)
1004	Expressway	pcu/period	20	Bus	
1004	Expressway	pcu/period	91	FeederCar	
1004	Expressway	pcu/period	92	FeederBus	
1004	Expressway	pcu/period	93	FeederWalk	
1004	Expressway	pcu/period	94	FeegerCycl	
1004	Expressway	pcu/period	95	FeederUnd	
1006	Expressway	pcu/period	10	Car	Jing Zang (G6)
1006	Expressway	pcu/period	20	Bus	
1006	Expressway	pcu/period	91	FeederCar	
1006	Expressway	pcu/period	92	FeederBus	
1006	Expressway	pcu/period	93	FeederWalk	
1006	Expressway	pcu/period	94	FeegerCycl	
1006	Expressway	pcu/period	95	FeederUnd	
1012	Expressway	pcu/period	10	Car	Beijing Airport (S12)
1012	Expressway	pcu/period	20	Bus	
1012	Expressway	pcu/period	91	FeederCar	
1012	Expressway	pcu/period	92	FeederBus	
1012	Expressway	pcu/period	93	FeederWalk	
1012	Expressway	pcu/period	94	FeegerCycl	
1012	Expressway	pcu/period	95	FeederUnd	
1028	Expressway	pcu/period	10	Car	Beijing Airport North Line (S28)
1028	Expressway	pcu/period	20	Bus	
1028	Expressway	pcu/period	91	FeederCar	
1028	Expressway	pcu/period	92	FeederBus	
1028	Expressway	pcu/period	93	FeederWalk	
1028	Expressway	pcu/period	94	FeegerCycl	
1028	Expressway	pcu/period	95	FeederUnd	
1030	Expressway	pcu/period	10	Car	Jing Jin (S30)
1030	Expressway	pcu/period	20	Bus	
1030	Expressway	pcu/period	91	FeederCar	
1030	Expressway	pcu/period	92	FeederBus	
1030	Expressway	pcu/period	93	FeederWalk	
1030	Expressway	pcu/period	94	FeegerCycl	
1030	Expressway	pcu/period	95	FeederUnd	
1032	Expressway	pcu/period	10	Car	Jing Ping (S32)
1032	Expressway	pcu/period	20	Bus	
1032	Expressway	pcu/period	91	FeederCar	
1032	Expressway	pcu/period	92	FeederBus	
1032	Expressway	pcu/period	93	FeederWalk	
1032	Expressway	pcu/period	94	FeegerCycl	
1032	Expressway	pcu/period	95	FeederUnd	
1051	Expressway	pcu/period	10	Car	Airport 2nd Expressway (S51)
1051	Expressway	pcu/period	20	Bus	

Type	Type Name	Unit	Mode	Mode Name	Description
1051	Expressway	pcu/period	91	FeederCar	
1051	Expressway	pcu/period	92	FeederBus	
1051	Expressway	pcu/period	93	FeederWalk	
1051	Expressway	pcu/period	94	FeegerCycl	
1051	Expressway	pcu/period	95	FeederUnd	
1101	Expressway	pcu/period	10	Car	Jing Jin (S1)
1101	Expressway	pcu/period	20	Bus	
1101	Expressway	pcu/period	91	FeederCar	
1101	Expressway	pcu/period	92	FeederBus	
1101	Expressway	pcu/period	93	FeederWalk	
1101	Expressway	pcu/period	94	FeegerCycl	
1101	Expressway	pcu/period	95	FeederUnd	
1102	Expressway	pcu/period	10	Car	Jing Tong (G102)
1102	Expressway	pcu/period	20	Bus	
1102	Expressway	pcu/period	91	FeederCar	
1102	Expressway	pcu/period	92	FeederBus	
1102	Expressway	pcu/period	93	FeederWalk	
1102	Expressway	pcu/period	94	FeegerCycl	
1102	Expressway	pcu/period	95	FeederUnd	
1106	Expressway	pcu/period	10	Car	Jing Kai (G106, part of G45)
1106	Expressway	pcu/period	20	Bus	
1106	Expressway	pcu/period	91	FeederCar	
1106	Expressway	pcu/period	92	FeederBus	
1106	Expressway	pcu/period	93	FeederWalk	
1106	Expressway	pcu/period	94	FeegerCycl	
1106	Expressway	pcu/period	95	FeederUnd	
1111	Expressway	pcu/period	10	Car	Jing Cheng (S11, part of G45)
1111	Expressway	pcu/period	20	Bus	
1111	Expressway	pcu/period	91	FeederCar	
1111	Expressway	pcu/period	92	FeederBus	
1111	Expressway	pcu/period	93	FeederWalk	
1111	Expressway	pcu/period	94	FeegerCycl	
1111	Expressway	pcu/period	95	FeederUnd	
5001	Expressway	pcu/period	10	Car	Other expressways outside Beijing
5001	Expressway	pcu/period	20	Bus	
5001	Expressway	pcu/period	91	FeederCar	
5001	Expressway	pcu/period	92	FeederBus	
5001	Expressway	pcu/period	93	FeederWalk	
5001	Expressway	pcu/period	94	FeegerCycl	
5001	Expressway	pcu/period	95	FeederUnd	

Table A2.3. Urban Road Link Type

Type	Type Name	Unit	Mode	Mode Name	Description
3200	RingRoad	pcu/period	10	Car	Beijing 2nd Ring Road
3200	RingRoad	pcu/period	20	Bus	
3200	RingRoad	pcu/period	91	FeederCar	
3200	RingRoad	pcu/period	92	FeederBus	
3200	RingRoad	pcu/period	93	FeederWalk	
3200	RingRoad	pcu/period	94	FeegerCycl	
3200	RingRoad	pcu/period	95	FeederUnd	
3300	RingRoad	pcu/period	10	Car	Beijing 3rd Ring Road
3300	RingRoad	pcu/period	20	Bus	
3300	RingRoad	pcu/period	91	FeederCar	
3300	RingRoad	pcu/period	92	FeederBus	
3300	RingRoad	pcu/period	93	FeederWalk	
3300	RingRoad	pcu/period	94	FeegerCycl	
3300	RingRoad	pcu/period	95	FeederUnd	
3400	RingRoad	pcu/period	10	Car	Beijing 4th Ring Road
3400	RingRoad	pcu/period	20	Bus	
3400	RingRoad	pcu/period	91	FeederCar	
3400	RingRoad	pcu/period	92	FeederBus	
3400	RingRoad	pcu/period	93	FeederWalk	
3400	RingRoad	pcu/period	94	FeegerCycl	
3400	RingRoad	pcu/period	95	FeederUnd	
3500	RingRoad	pcu/period	10	Car	Beijing 5th Ring Road
3500	RingRoad	pcu/period	20	Bus	
3500	RingRoad	pcu/period	91	FeederCar	
3500	RingRoad	pcu/period	92	FeederBus	
3500	RingRoad	pcu/period	93	FeederWalk	
3500	RingRoad	pcu/period	94	FeegerCycl	
3500	RingRoad	pcu/period	95	FeederUnd	
3600	RingRoad	pcu/period	10	Car	Beijing 6th Ring Road
3600	RingRoad	pcu/period	20	Bus	
3600	RingRoad	pcu/period	91	FeederCar	
3600	RingRoad	pcu/period	92	FeederBus	
3600	RingRoad	pcu/period	93	FeederWalk	
3600	RingRoad	pcu/period	94	FeegerCycl	
3600	RingRoad	pcu/period	95	FeederUnd	
3201	ClassOne	pcu/period	10	Car	Level 1 major links within 2nd Ring Road
3201	ClassOne	pcu/period	20	Bus	
3201	ClassOne	pcu/period	40	Cycle	
3201	ClassOne	pcu/period	91	FeederCar	
3201	ClassOne	pcu/period	92	FeederBus	
3201	ClassOne	pcu/period	93	FeederWalk	
3201	ClassOne	pcu/period	94	FeegerCycl	
3201	ClassOne	pcu/period	95	FeederUnd	
3301	ClassOne	pcu/period	10	Car	Level 1 major links between 2nd and 3rd Ring Road
3301	ClassOne	pcu/period	20	Bus	
3301	ClassOne	pcu/period	40	Cycle	
3301	ClassOne	pcu/period	91	FeederCar	
3301	ClassOne	pcu/period	92	FeederBus	
3301	ClassOne	pcu/period	93	FeederWalk	
3301	ClassOne	pcu/period	94	FeegerCycl	
3301	ClassOne	pcu/period	95	FeederUnd	
3401	ClassOne	pcu/period	10	Car	Level 1 major links between 3rd and 4th Ring Road
3401	ClassOne	pcu/period	20	Bus	
3401	ClassOne	pcu/period	40	Cycle	
3401	ClassOne	pcu/period	91	FeederCar	
3401	ClassOne	pcu/period	92	FeederBus	

Type	Type Name	Unit	Mode	Mode Name	Description
3401	ClassOne	pcu/period	93	FeederWalk	
3401	ClassOne	pcu/period	94	FeegerCycl	
3401	ClassOne	pcu/period	95	FeederUnd	
3501	ClassOne	pcu/period	10	Car	Level 1 major links between 4th and 5th Ring Road
3501	ClassOne	pcu/period	20	Bus	
3501	ClassOne	pcu/period	40	Cycle	
3501	ClassOne	pcu/period	91	FeederCar	
3501	ClassOne	pcu/period	92	FeederBus	
3501	ClassOne	pcu/period	93	FeederWalk	
3501	ClassOne	pcu/period	94	FeegerCycl	
3501	ClassOne	pcu/period	95	FeederUnd	
3601	ClassOne	pcu/period	10	Car	Level 1 major links between 5th and 6th Ring Road
3601	ClassOne	pcu/period	20	Bus	
3601	ClassOne	pcu/period	40	Cycle	
3601	ClassOne	pcu/period	91	FeederCar	
3601	ClassOne	pcu/period	92	FeederBus	
3601	ClassOne	pcu/period	93	FeederWalk	
3601	ClassOne	pcu/period	94	FeegerCycl	
3601	ClassOne	pcu/period	95	FeederUnd	
5002	ClassOne	pcu/period	10	Car	Level 1 major links outside Beijing
5002	ClassOne	pcu/period	20	Bus	
5002	ClassOne	pcu/period	40	Cycle	
5002	ClassOne	pcu/period	91	FeederCar	
5002	ClassOne	pcu/period	92	FeederBus	
5002	ClassOne	pcu/period	93	FeederWalk	
5002	ClassOne	pcu/period	94	FeegerCycl	
5002	ClassOne	pcu/period	95	FeederUnd	
3203	ClassTwo	pcu/period	10	Car	Level 2 major links within 2nd Ring Road
3203	ClassTwo	pcu/period	20	Bus	
3203	ClassTwo	pcu/period	30	Walk	
3203	ClassTwo	pcu/period	40	Cycle	
3203	ClassTwo	pcu/period	91	FeederCar	
3203	ClassTwo	pcu/period	92	FeederBus	
3203	ClassTwo	pcu/period	93	FeederWalk	
3203	ClassTwo	pcu/period	94	FeegerCycl	
3203	ClassTwo	pcu/period	95	FeederUnd	
3303	ClassTwo	pcu/period	10	Car	Level 2 major links between 2nd and 3rd Ring Road
3303	ClassTwo	pcu/period	20	Bus	
3303	ClassTwo	pcu/period	30	Walk	
3303	ClassTwo	pcu/period	40	Cycle	
3303	ClassTwo	pcu/period	91	FeederCar	
3303	ClassTwo	pcu/period	92	FeederBus	
3303	ClassTwo	pcu/period	93	FeederWalk	
3303	ClassTwo	pcu/period	94	FeegerCycl	
3303	ClassTwo	pcu/period	95	FeederUnd	
3403	ClassTwo	pcu/period	10	Car	Level 2 major links between 3rd and 4th Ring Road
3403	ClassTwo	pcu/period	20	Bus	
3403	ClassTwo	pcu/period	30	Walk	
3403	ClassTwo	pcu/period	40	Cycle	
3403	ClassTwo	pcu/period	91	FeederCar	
3403	ClassTwo	pcu/period	92	FeederBus	
3403	ClassTwo	pcu/period	93	FeederWalk	
3403	ClassTwo	pcu/period	94	FeegerCycl	
3403	ClassTwo	pcu/period	95	FeederUnd	

Type	Type Name	Unit	Mode	Mode Name	Description
3503	ClassTwo	pcu/period	10	Car	Level 2 major links between 4th and 5th Ring Road
3503	ClassTwo	pcu/period	20	Bus	
3503	ClassTwo	pcu/period	30	Walk	
3503	ClassTwo	pcu/period	40	Cycle	
3503	ClassTwo	pcu/period	91	FeederCar	
3503	ClassTwo	pcu/period	92	FeederBus	
3503	ClassTwo	pcu/period	93	FeederWalk	
3503	ClassTwo	pcu/period	94	FeegerCycl	
3503	ClassTwo	pcu/period	95	FeederUnd	
3603	ClassTwo	pcu/period	10	Car	Level 2 major links between 5th and 6th Ring Road
3603	ClassTwo	pcu/period	20	Bus	
3603	ClassTwo	pcu/period	30	Walk	
3603	ClassTwo	pcu/period	40	Cycle	
3603	ClassTwo	pcu/period	91	FeederCar	
3603	ClassTwo	pcu/period	92	FeederBus	
3603	ClassTwo	pcu/period	93	FeederWalk	
3603	ClassTwo	pcu/period	94	FeegerCycl	
3603	ClassTwo	pcu/period	95	FeederUnd	
5003	ClassTwo	pcu/period	10	Car	Level 2 major links outside Beijing
5003	ClassTwo	pcu/period	20	Bus	
5003	ClassTwo	pcu/period	30	Walk	
5003	ClassTwo	pcu/period	40	Cycle	
5003	ClassTwo	pcu/period	91	FeederCar	
5003	ClassTwo	pcu/period	92	FeederBus	
5003	ClassTwo	pcu/period	93	FeederWalk	
5003	ClassTwo	pcu/period	94	FeegerCycl	
5003	ClassTwo	pcu/period	95	FeederUnd	
3205	ClassThre	pcu/period	10	Car	Level 3 major links within 2nd Ring Road
3205	ClassThre	pcu/period	20	Bus	
3205	ClassThre	pcu/period	30	Walk	
3205	ClassThre	pcu/period	40	Cycle	
3205	ClassThre	pcu/period	91	FeederCar	
3205	ClassThre	pcu/period	92	FeederBus	
3205	ClassThre	pcu/period	93	FeederWalk	
3205	ClassThre	pcu/period	94	FeegerCycl	
3205	ClassThre	pcu/period	95	FeederUnd	
3305	ClassThre	pcu/period	10	Car	Level 3 major links between 2nd and 3rd Ring Road
3305	ClassThre	pcu/period	20	Bus	
3305	ClassThre	pcu/period	30	Walk	
3305	ClassThre	pcu/period	40	Cycle	
3305	ClassThre	pcu/period	91	FeederCar	
3305	ClassThre	pcu/period	92	FeederBus	
3305	ClassThre	pcu/period	93	FeederWalk	
3305	ClassThre	pcu/period	94	FeegerCycl	
3305	ClassThre	pcu/period	95	FeederUnd	
3405	ClassThre	pcu/period	10	Car	Level 3 major links between 3rd and 4th Ring Road
3405	ClassThre	pcu/period	20	Bus	
3405	ClassThre	pcu/period	30	Walk	
3405	ClassThre	pcu/period	40	Cycle	
3405	ClassThre	pcu/period	91	FeederCar	
3405	ClassThre	pcu/period	92	FeederBus	
3405	ClassThre	pcu/period	93	FeederWalk	
3405	ClassThre	pcu/period	94	FeegerCycl	
3405	ClassThre	pcu/period	95	FeederUnd	

Type	Type Name	Unit	Mode	Mode Name	Description
3505	ClassThre	pcu/period	10	Car	Level 3 major links between 4th and 5th Ring Road
3505	ClassThre	pcu/period	20	Bus	
3505	ClassThre	pcu/period	30	Walk	
3505	ClassThre	pcu/period	40	Cycle	
3505	ClassThre	pcu/period	91	FeederCar	
3505	ClassThre	pcu/period	92	FeederBus	
3505	ClassThre	pcu/period	93	FeederWalk	
3505	ClassThre	pcu/period	94	FeegerCycl	
3505	ClassThre	pcu/period	95	FeederUnd	
3605	ClassThre	pcu/period	10	Car	Level 3 major links between 5th and 6th Ring Road
3605	ClassThre	pcu/period	20	Bus	
3605	ClassThre	pcu/period	30	Walk	
3605	ClassThre	pcu/period	40	Cycle	
3605	ClassThre	pcu/period	91	FeederCar	
3605	ClassThre	pcu/period	92	FeederBus	
3605	ClassThre	pcu/period	93	FeederWalk	
3605	ClassThre	pcu/period	94	FeegerCycl	
3605	ClassThre	pcu/period	95	FeederUnd	
5004	ClassThre	pcu/period	10	Car	Level 3 major links outside Beijing
5004	ClassThre	pcu/period	20	Bus	
5004	ClassThre	pcu/period	30	Walk	
5004	ClassThre	pcu/period	40	Cycle	
5004	ClassThre	pcu/period	91	FeederCar	
5004	ClassThre	pcu/period	92	FeederBus	
5004	ClassThre	pcu/period	93	FeederWalk	
5004	ClassThre	pcu/period	94	FeegerCycl	
5004	ClassThre	pcu/period	95	FeederUnd	
3207	ClassFour	pcu/period	10	Car	Level 4 major links within 2nd Ring Road
3207	ClassFour	pcu/period	20	Bus	
3207	ClassFour	pcu/period	30	Walk	
3207	ClassFour	pcu/period	40	Cycle	
3207	ClassFour	pcu/period	91	FeederCar	
3207	ClassFour	pcu/period	92	FeederBus	
3207	ClassFour	pcu/period	93	FeederWalk	
3207	ClassFour	pcu/period	94	FeegerCycl	
3207	ClassFour	pcu/period	95	FeederUnd	
3307	ClassFour	pcu/period	10	Car	Level 4 major links between 2nd and 3rd Ring Road
3307	ClassFour	pcu/period	20	Bus	
3307	ClassFour	pcu/period	30	Walk	
3307	ClassFour	pcu/period	40	Cycle	
3307	ClassFour	pcu/period	91	FeederCar	
3307	ClassFour	pcu/period	92	FeederBus	
3307	ClassFour	pcu/period	93	FeederWalk	
3307	ClassFour	pcu/period	94	FeegerCycl	
3307	ClassFour	pcu/period	95	FeederUnd	
3407	ClassFour	pcu/period	10	Car	Level 4 major links between 3rd and 4th Ring Road
3407	ClassFour	pcu/period	20	Bus	
3407	ClassFour	pcu/period	30	Walk	
3407	ClassFour	pcu/period	40	Cycle	
3407	ClassFour	pcu/period	91	FeederCar	
3407	ClassFour	pcu/period	92	FeederBus	
3407	ClassFour	pcu/period	93	FeederWalk	
3407	ClassFour	pcu/period	94	FeegerCycl	
3407	ClassFour	pcu/period	95	FeederUnd	

Type	Type Name	Unit	Mode	Mode Name	Description
3507	ClassFour	pcu/period	10	Car	Level 4 major links between 4th and 5th Ring Road
3507	ClassFour	pcu/period	20	Bus	
3507	ClassFour	pcu/period	30	Walk	
3507	ClassFour	pcu/period	40	Cycle	
3507	ClassFour	pcu/period	91	FeederCar	
3507	ClassFour	pcu/period	92	FeederBus	
3507	ClassFour	pcu/period	93	FeederWalk	
3507	ClassFour	pcu/period	94	FeegerCycl	
3507	ClassFour	pcu/period	95	FeederUnd	
3607	ClassFour	pcu/period	10	Car	Level 4 major links between 5th and 6th Ring Road
3607	ClassFour	pcu/period	20	Bus	
3607	ClassFour	pcu/period	30	Walk	
3607	ClassFour	pcu/period	40	Cycle	
3607	ClassFour	pcu/period	91	FeederCar	
3607	ClassFour	pcu/period	92	FeederBus	
3607	ClassFour	pcu/period	93	FeederWalk	
3607	ClassFour	pcu/period	94	FeegerCycl	
3607	ClassFour	pcu/period	95	FeederUnd	
5005	ClassFour	pcu/period	10	Car	Level 4 major links outside Beijing
5005	ClassFour	pcu/period	20	Bus	
5005	ClassFour	pcu/period	30	Walk	
5005	ClassFour	pcu/period	40	Cycle	
5005	ClassFour	pcu/period	91	FeederCar	
5005	ClassFour	pcu/period	92	FeederBus	
5005	ClassFour	pcu/period	93	FeederWalk	
5005	ClassFour	pcu/period	94	FeegerCycl	
5005	ClassFour	pcu/period	95	FeederUnd	

Table A2.4. Metro Link Type

Type	Type Name	Unit	Mode	Mode Name	Description
6501	BJUndergr	person	60	Underg	Line 1
6501	BJUndergr	person	95	FeederUnd	
6502	BJUndergr	person	60	Underg	Line 2
6502	BJUndergr	person	95	FeederUnd	
6503	BJUndergr	person	60	Underg	Line 3
6503	BJUndergr	person	95	FeederUnd	
6504	BJUndergr	person	60	Underg	Line 4 + Da Xing Line
6504	BJUndergr	person	95	FeederUnd	
6505	BJUndergr	person	60	Underg	Line 5 + Yi Zhuang Line
6505	BJUndergr	person	95	FeederUnd	
6506	BJUndergr	person	60	Underg	Line 6
6506	BJUndergr	person	95	FeederUnd	
6507	BJUndergr	person	60	Underg	Line 7
6507	BJUndergr	person	95	FeederUnd	
6508	BJUndergr	person	60	Underg	Line 8
6508	BJUndergr	person	95	FeederUnd	
6509	BJUndergr	person	60	Underg	Line 9
6509	BJUndergr	person	95	FeederUnd	
6510	BJUndergr	person	60	Underg	Line 10
6510	BJUndergr	person	95	FeederUnd	
6511	BJUndergr	person	60	Underg	Line 11
6511	BJUndergr	person	95	FeederUnd	
6512	BJUndergr	person	60	Underg	Line 12
6512	BJUndergr	person	95	FeederUnd	
6513	BJUndergr	person	60	Underg	Line 13
6513	BJUndergr	person	95	FeederUnd	
6514	BJUndergr	person	60	Underg	Line 14
6514	BJUndergr	person	95	FeederUnd	
6515	BJUndergr	person	60	Underg	Line 15
6515	BJUndergr	person	95	FeederUnd	
6516	BJUndergr	person	60	Underg	Line 16
6516	BJUndergr	person	95	FeederUnd	
6517	BJUndergr	person	60	Underg	Line 17
6517	BJUndergr	person	95	FeederUnd	
6519	BJUndergr	person	60	Underg	Line 19
6519	BJUndergr	person	95	FeederUnd	
6520	BJUndergr	person	60	Underg	Line 20
6520	BJUndergr	person	95	FeederUnd	
6521	BJUndergr	person	60	Underg	Line 21
6521	BJUndergr	person	95	FeederUnd	
6530	BJUndergr	person	60	Underg	Airport line
6530	BJUndergr	person	95	FeederUnd	
6535	BJUndergr	person	60	Underg	Chang Ping line
6535	BJUndergr	person	95	FeederUnd	
6537	BJUndergr	person	60	Underg	Fang Shan line
6537	BJUndergr	person	95	FeederUnd	
6541	BJUndergr	person	60	Underg	Men Tou Gou line
6541	BJUndergr	person	95	FeederUnd	
6543	BJUndergr	person	60	Underg	Yan Fang line
6543	BJUndergr	person	95	FeederUnd	
6545	BJUndergr	person	60	Underg	Xi Jiao line
6545	BJUndergr	person	95	FeederUnd	
6601	TJUndergr	person	60	Underg	Tianjin Line 1
6601	TJUndergr	person	95	FeederUnd	
6602	TJUndergr	person	60	Underg	Tianjin Line 2
6602	TJUndergr	person	95	FeederUnd	
6603	TJUndergr	person	60	Underg	Tianjin Line 3
6603	TJUndergr	person	95	FeederUnd	

Type	Type Name	Unit	Mode	Mode Name	Description
6609	TJUndergr	person	60	Underg	Tianjin Line 9
6609	TJUndergr	person	95	FeederUnd	
6641	TJUndergr	person	60	Underg	Tianjin Binhai New Zone line
6641	TJUndergr	person	95	FeederUnd	
6699	TJUndergr	person	60	Underg	Tianjin Suburban Tram
6699	TJUndergr	person	95	FeederUnd	

Table A2.5. Rail Link Type

Type	Type Name	Unit	Mode	Mode Name	Description
6801	Railway	person	50	Rail	Jing Hu line
6802	Railway	person	50	Rail	Jing Jiu line
6803	Railway	person	50	Rail	Jing Guang line
6804	Railway	person	50	Rail	Jiao Liu line
6805	Railway	person	50	Rail	Jing Ha line
6806	Railway	person	50	Rail	Jing Tong line
6811	Railway	person	50	Rail	Jing Bao line
6812	Railway	person	50	Rail	Jing Yuan line
6813	Railway	person	50	Rail	Jing Cheng line
6814	Railway	person	50	Rail	Jing Qin line
6815	Railway	person	50	Rail	Jin Ji line
6901	HSRail	person	70	HSRail	High speed rail: Beijing-Shanghai
6902	HSRail	person	70	HSRail	High speed rail: Beijing-Shijiazhuang-Wuhan
6903	HSRail	person	70	HSRail	High speed rail: Harbin-Dalian
6907	HSRail	person	70	HSRail	High speed rail: Taiyuan-Shijiazhuang-Jinan-Qindao
6911	HSRail	person	70	HSRail	High speed rail: Qinhuangdao-Shenyang
6914	HSRail	person	70	HSRail	High speed rail: Beijing-Tianjin
6919	HSRail	person	70	HSRail	High speed rail: Tianjin-Qinhuangdao
6990	HSRail	person	70	HSRail	High speed rail: Future Lines (not included in 2010 model)

Table A2.6. Access Link Type

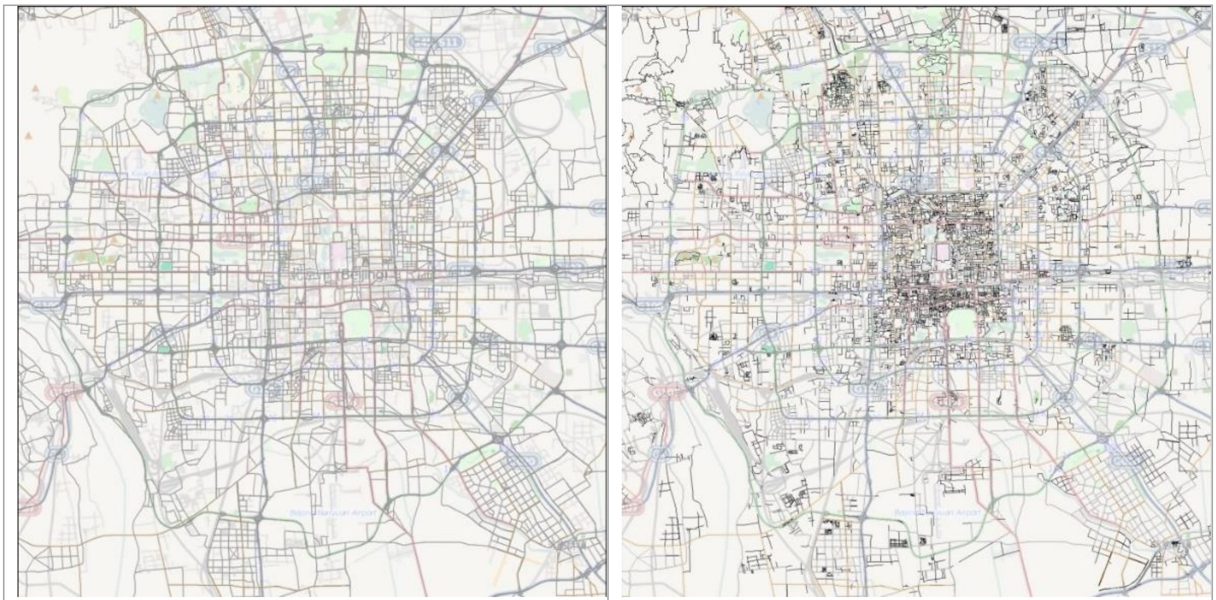
Type	Type Name	Unit	Mode	Mode Name	Description
8001	Cen 2 Jun	pcu/period	10	Car	Access between zonal centroid and road junction
8001	Cen 2 Jun	pcu/period	20	Bus	
8001	Cen 2 Jun	pcu/period	30	Walk	
8001	Cen 2 Jun	pcu/period	40	Cycle	
8001	Cen 2 Jun	pcu/period	60	Underg	
8001	Cen 2 Jun	pcu/period	91	FeederCar	
8001	Cen 2 Jun	pcu/period	92	FeederBus	
8001	Cen 2 Jun	pcu/period	93	FeederWalk	
8001	Cen 2 Jun	pcu/period	94	FeegerCycl	
8001	Cen 2 Jun	pcu/period	101	IntraCar	
8001	Cen 2 Jun	pcu/period	102	IntraCar	
8001	Cen 2 Jun	pcu/period	103	IntraCar	
8001	Cen 2 Jun	pcu/period	104	IntraCar	
8001	Cen 2 Jun	pcu/period	105	IntraCar	
8001	Cen 2 Jun	pcu/period	106	IntraCar	
8001	Cen 2 Jun	pcu/period	107	IntraCar	
8001	Cen 2 Jun	pcu/period	108	IntraCar	
8001	Cen 2 Jun	pcu/period	109	IntraCar	
8001	Cen 2 Jun	pcu/period	111	IntraBus	
8001	Cen 2 Jun	pcu/period	112	IntraBus	
8001	Cen 2 Jun	pcu/period	113	IntraBus	
8001	Cen 2 Jun	pcu/period	114	IntraBus	
8001	Cen 2 Jun	pcu/period	115	IntraBus	
8001	Cen 2 Jun	pcu/period	116	IntraBus	
8001	Cen 2 Jun	pcu/period	117	IntraBus	
8001	Cen 2 Jun	pcu/period	118	IntraBus	
8001	Cen 2 Jun	pcu/period	119	IntraBus	
8001	Cen 2 Jun	pcu/period	121	IntraWalk	
8001	Cen 2 Jun	pcu/period	122	IntraWalk	
8001	Cen 2 Jun	pcu/period	123	IntraWalk	
8001	Cen 2 Jun	pcu/period	131	IntraCycle	
8001	Cen 2 Jun	pcu/period	132	IntraCycle	
8001	Cen 2 Jun	pcu/period	133	IntraCycle	
8001	Cen 2 Jun	pcu/period	134	IntraCycle	
8001	Cen 2 Jun	pcu/period	135	IntraCycle	
8301	Rail 2 Cen	pcu/period	10	Car	Access between railway zonal centroid and railway station
8301	Rail 2 Cen	pcu/period	20	Bus	
8301	Rail 2 Cen	pcu/period	30	Walk	
8301	Rail 2 Cen	pcu/period	40	Cycle	
8301	Rail 2 Cen	pcu/period	60	Underg	
8301	Rail 2 Cen	pcu/period	91	FeederCar	
8301	Rail 2 Cen	pcu/period	92	FeederBus	
8301	Rail 2 Cen	pcu/period	93	FeederWalk	
8301	Rail 2 Cen	pcu/period	94	FeegerCycl	
8301	Rail 2 Cen	pcu/period	141	IntraRail	
8301	Rail 2 Cen	pcu/period	142	IntraRail	
8301	Rail 2 Cen	pcu/period	143	IntraRail	
8301	Rail 2 Cen	pcu/period	144	IntraRail	
8301	Rail 2 Cen	pcu/period	145	IntraRail	
8301	Rail 2 Cen	pcu/period	146	IntraRail	
8301	Rail 2 Cen	pcu/period	147	IntraRail	
8301	Rail 2 Cen	pcu/period	148	IntraRail	
8301	Rail 2 Cen	pcu/period	149	IntraRail	
8302	Rail 2 Jun	pcu/period	10	Car	Access between railway station and road junction
8302	Rail 2 Jun	pcu/period	20	Bus	
8302	Rail 2 Jun	pcu/period	30	Walk	
8302	Rail 2 Jun	pcu/period	40	Cycle	

Type	Type Name	Unit	Mode	Mode Name	Description
8302	Rail 2 Jun	pcu/period	60	Underg	
8302	Rail 2 Jun	pcu/period	91	FeederCar	
8302	Rail 2 Jun	pcu/period	92	FeederBus	
8302	Rail 2 Jun	pcu/period	93	FeederWalk	
8302	Rail 2 Jun	pcu/period	94	FeegerCycl	
8305	Rail 2 Sub	pcu/period	10	Car	Access between railway station and Beijing subway station
8305	Rail 2 Sub	pcu/period	20	Bus	
8305	Rail 2 Sub	pcu/period	30	Walk	
8305	Rail 2 Sub	pcu/period	40	Cycle	
8305	Rail 2 Sub	pcu/period	84	SubTrans	
8305	Rail 2 Sub	pcu/period	91	FeederCar	
8305	Rail 2 Sub	pcu/period	92	FeederBus	
8305	Rail 2 Sub	pcu/period	93	FeederWalk	
8305	Rail 2 Sub	pcu/period	94	FeegerCycl	
8306	Rail 2 Sub	pcu/period	10	Car	Access between railway station and Tianjin subway station
8306	Rail 2 Sub	pcu/period	20	Bus	
8306	Rail 2 Sub	pcu/period	30	Walk	
8306	Rail 2 Sub	pcu/period	40	Cycle	
8306	Rail 2 Sub	pcu/period	84	SubTrans	
8306	Rail 2 Sub	pcu/period	91	FeederCar	
8306	Rail 2 Sub	pcu/period	92	FeederBus	
8306	Rail 2 Sub	pcu/period	93	FeederWalk	
8306	Rail 2 Sub	pcu/period	94	FeegerCycl	
8501	BJSub2 cen	pcu/period	10	Car	Access between centroid and Beijing subway station
8501	BJSub2 cen	pcu/period	20	Bus	
8501	BJSub2 cen	pcu/period	30	Walk	
8501	BJSub2 cen	pcu/period	40	Cycle	
8501	BJSub2 cen	pcu/period	60	Underg	
8501	BJSub2 cen	pcu/period	91	FeederCar	
8501	BJSub2 cen	pcu/period	92	FeederBus	
8501	BJSub2 cen	pcu/period	93	FeederWalk	
8501	BJSub2 cen	pcu/period	94	FeegerCycl	
8501	BJSub2 cen	pcu/period	141	IntraRail	
8501	BJSub2 cen	pcu/period	142	IntraRail	
8501	BJSub2 cen	pcu/period	143	IntraRail	
8501	BJSub2 cen	pcu/period	144	IntraRail	
8501	BJSub2 cen	pcu/period	145	IntraRail	
8501	BJSub2 cen	pcu/period	146	IntraRail	
8501	BJSub2 cen	pcu/period	147	IntraRail	
8501	BJSub2 cen	pcu/period	148	IntraRail	
8501	BJSub2 cen	pcu/period	149	IntraRail	
8502	BJSub2 Jun	pcu/period	10	Car	Access between road junction and Beijing subway station
8502	BJSub2 Jun	pcu/period	20	Bus	
8502	BJSub2 Jun	pcu/period	30	Walk	
8502	BJSub2 Jun	pcu/period	40	Cycle	
8502	BJSub2 Jun	pcu/period	60	Underg	
8502	BJSub2 Jun	pcu/period	91	FeederCar	
8502	BJSub2 Jun	pcu/period	92	FeederBus	
8502	BJSub2 Jun	pcu/period	93	FeederWalk	
8502	BJSub2 Jun	pcu/period	94	FeegerCycl	
8503	BJSub Tran	pcu/period	10	Car	Access between Beijing subway stations
8503	BJSub Tran	pcu/period	20	Bus	
8503	BJSub Tran	pcu/period	30	Walk	
8503	BJSub Tran	pcu/period	40	Cycle	
8503	BJSub Tran	pcu/period	84	SubTrans	

Type	Type Name	Unit	Mode	Mode Name	Description
8503	BJSub Tran	pcu/period	91	FeederCar	
8503	BJSub Tran	pcu/period	92	FeederBus	
8503	BJSub Tran	pcu/period	93	FeederWalk	
8503	BJSub Tran	pcu/period	94	FeegerCycl	
8601	TJSub2 Cen	pcu/period	10	Car	Access Between centroid and Tianjin subway station
8601	TJSub2 Cen	pcu/period	20	Bus	
8601	TJSub2 Cen	pcu/period	30	Walk	
8601	TJSub2 Cen	pcu/period	40	Cycle	
8601	TJSub2 Cen	pcu/period	60	Underg	
8601	TJSub2 Cen	pcu/period	91	FeederCar	
8601	TJSub2 Cen	pcu/period	92	FeederBus	
8601	TJSub2 Cen	pcu/period	93	FeederWalk	
8601	TJSub2 Cen	pcu/period	94	FeegerCycl	
8602	TJSub2 Jun	pcu/period	10	Car	Access Between junction and Tianjin subway station
8602	TJSub2 Jun	pcu/period	20	Bus	
8602	TJSub2 Jun	pcu/period	30	Walk	
8602	TJSub2 Jun	pcu/period	40	Cycle	
8602	TJSub2 Jun	pcu/period	60	Underg	
8602	TJSub2 Jun	pcu/period	91	FeederCar	
8602	TJSub2 Jun	pcu/period	92	FeederBus	
8602	TJSub2 Jun	pcu/period	93	FeederWalk	
8602	TJSub2 Jun	pcu/period	94	FeegerCycl	

Appendix 3 Road network maps

This appendix documents three maps: (1) Initial map (**Figure A3.1(a)**) based on trunk links in the Open Street Map; (2) Infilled map (**Figure A3.1(b)**) with minor streets and unclassified roads; (3) Free flow speeds map (**Figure A3.2**).



(a) Initial map (b) Infilled map

Figure A3.1. Comparison of the initial and infilled road networks in the main built-up area of Beijing

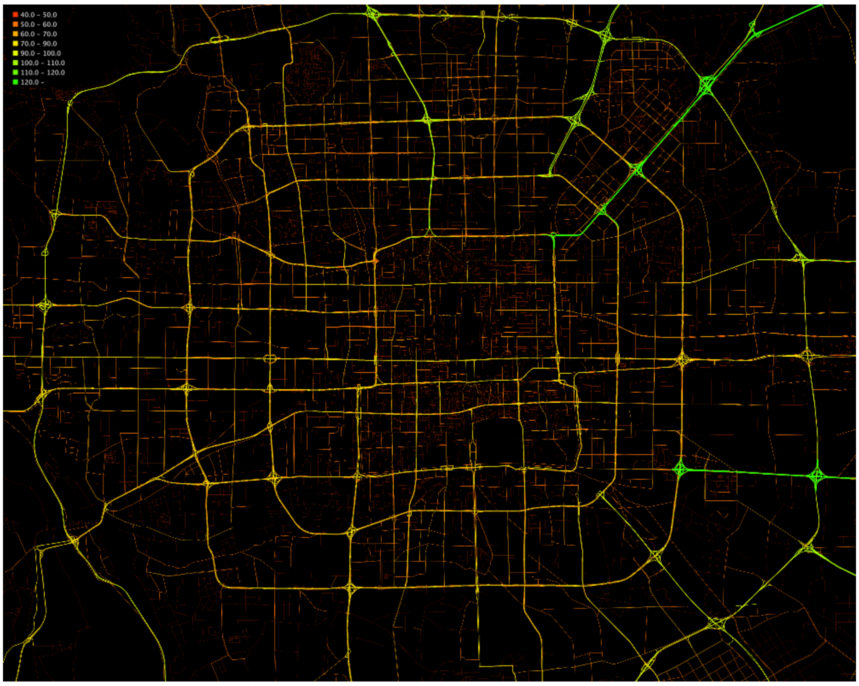


Figure A3.2. Free flow speeds of links in the road network in the main built-up area of Beijing

Appendix 4 Input data for intrazonal networks

Table A4.1. Data for generating the intrazonal networks

Model zone number	Radius for the built-up area	Radius for the entire zone	Metro availability from Band Number	Other rail availability from Band Number
1	3.63	5.19	2	6
2	3.53	4.42	2	6
3	3.43	3.43	2	6
4	3.60	3.60	2	6
10	3.25	4.07	2	6
11	2.61	2.90	2	6
12	5.40	6.00	2	6
13	2.42	3.02	2	6
14	2.23	2.23	2	6
15	3.87	4.30	2	6
16	2.99	2.99	2	6
17	2.45	2.45	2	6
18	6.19	7.74	2	6
19	2.10	2.10	2	6
20	3.61	4.51	2	6
21	5.84	7.30	2	6
22	3.06	3.06	2	6
23	4.46	4.96	2	6
24	2.66	2.66	2	6
25	4.13	4.13	2	6
26	2.80	2.80	2	6
27	3.00	3.00	2	6
28	2.31	2.31	2	6
29	1.53	1.53	2	6
30	2.11	2.11	2	6
31	2.84	2.84	2	6
32	1.78	1.78	2	6
33	3.00	3.00	2	6
34	2.87	2.87	2	6
35	4.70	4.70	2	6
36	4.00	4.00	2	6
37	3.59	3.59	2	6
38	3.94	3.94	2	6
39	2.70	2.70	2	6
40	4.45	4.45	2	6
41	3.84	3.84	2	6
42	1.55	1.55	2	6
43	2.95	2.95	2	6
44	1.21	1.21	2	6
45	1.23	1.23	2	6
46	2.11	2.11	2	6
47	3.96	3.96	2	6
48	3.00	3.00	2	6
49	4.32	4.32	2	6
50	2.80	2.80	2	6
51	4.32	4.32	2	6
52	4.00	4.00	2	6
53	5.83	7.29	2	6
54	5.02	5.02	2	6
55	4.01	4.01	2	6

Model zone number	Radius for the built-up area	Radius for the entire zone	Metro availability from Band Number	Other rail availability from Band Number
56	4.10	4.10	2	6
57	3.17	3.17	2	6
58	3.50	3.50	2	6
59	4.58	4.58	2	6
60	3.02	3.02	2	6
61	4.57	4.57	9	6
62	5.65	5.65	9	6
63	7.77	7.77	9	6
64	8.00	8.00	9	6
65	4.54	4.54	9	6
70	7.28	9.11	9	6
71	9.84	12.30	9	6
72	9.37	11.71	9	6
73	5.20	5.20	9	6
74	7.78	8.65	9	6
75	10.21	12.76	9	6
76	4.71	4.71	9	6
77	8.05	10.06	9	6
78	12.56	17.94	9	6
79	6.64	6.64	9	6
80	5.08	5.08	9	6
81	8.89	8.89	9	6
82	6.96	6.96	9	6
83	8.37	10.46	9	6
84	6.96	8.70	9	6
85	8.05	10.06	9	6
86	4.77	4.77	9	6
87	9.35	11.69	9	6
88	6.50	8.12	9	6
89	6.53	7.26	9	6
90	7.41	8.23	9	6
91	4.53	4.53	9	6
92	7.09	7.88	9	6
93	13.91	27.81	9	6
94	6.35	7.06	9	6
95	6.10	6.10	9	6
96	8.46	9.40	9	6
97	5.82	6.46	9	6
98	5.19	5.19	9	6
99	4.52	4.52	9	6
100	5.20	5.20	9	6
101	7.56	8.40	9	6
102	8.38	9.31	9	6
103	8.25	9.16	9	6
104	5.86	6.52	9	6
105	5.42	6.02	9	6
106	4.00	4.00	9	6
107	13.83	34.57	9	6
108	5.86	5.86	9	6
109	7.18	7.97	9	6
110	7.49	8.32	9	6
111	7.53	8.36	9	6
112	7.77	8.63	9	6
113	8.23	9.14	9	6

Model zone number	Radius for the built-up area	Radius for the entire zone	Metro availability from Band Number	Other rail availability from Band Number
114	6.11	6.79	9	6
115	4.28	8.57	9	6
116	6.68	7.42	9	6
117	9.44	13.49	9	6
118	8.70	12.43	9	6
119	6.46	6.46	9	6
120	10.09	14.42	9	6
121	9.30	10.33	9	6
122	9.77	13.96	9	6
123	9.62	13.74	9	6
124	7.75	9.69	9	6
125	10.59	15.13	9	6
126	11.00	12.23	9	6
127	8.52	9.47	9	6
128	5.83	5.83	9	6
129	11.37	14.21	9	6
130	9.95	19.90	9	6
131	8.96	8.96	9	6
132	9.68	19.35	9	6
133	7.80	9.75	9	6
134	8.85	17.71	9	6
135	9.26	13.22	9	6
136	9.24	23.11	9	6
137	11.26	37.53	9	6
138	12.31	41.05	9	6
150	10.60	26.51	9	6
152	10.40	20.80	9	6
156	9.45	18.90	9	6
159	9.51	10.57	9	6
161	5.29	5.29	9	6
162	7.93	7.93	9	6
163	8.63	8.63	9	6
168	9.59	13.71	9	6
170	8.36	10.46	9	6
171	7.56	7.56	9	6
172	10.03	11.14	9	6
174	8.22	10.28	9	6
175	8.40	12.00	9	6
176	7.90	9.88	9	6
177	8.21	8.21	9	6
178	7.89	7.89	9	6
179	7.56	7.56	9	6
180	9.12	9.12	9	6
181	9.34	9.34	9	6
182	8.90	11.12	9	6
183	8.74	8.74	9	6
184	7.26	7.26	9	6
185	9.59	13.69	9	6
186	8.64	10.80	9	6
187	8.44	10.55	9	6
188	11.28	37.61	9	6
189	9.54	11.93	9	6
191	9.57	13.67	9	6
192	9.23	11.53	9	6

Model zone number	Radius for the built-up area	Radius for the entire zone	Metro availability from Band Number	Other rail availability from Band Number
193	8.99	11.24	9	6
194	6.64	6.64	9	6
195	8.08	11.54	9	6
196	7.91	11.30	9	6
197	8.21	9.12	9	6
198	5.39	5.39	9	6
199	3.81	3.81	9	6
201	7.64	7.64	9	6
202	6.04	6.04	9	6
204	7.50	7.50	9	6
205	5.56	5.56	9	6
206	5.48	5.48	9	6
207	12.29	40.97	9	6
208	10.67	11.85	9	6
209	5.33	5.33	9	6
211	6.64	6.64	9	6
215	7.18	7.18	9	6
216	7.00	7.00	9	6
217	9.58	10.64	9	6
219	7.63	7.63	9	6
250	8.17	16.33	9	6
251	9.42	117.79	9	6
256	8.37	8.37	9	6
257	8.21	102.69	9	6
261	9.49	9.49	9	6
262	9.01	112.61	9	6
269	8.87	88.66	9	6
273	7.88	71.63	9	6
274	7.88	7.88	9	6
275	9.17	114.62	9	6
282	8.73	10.91	9	6
284	15.00	130.50	9	6
291	15.00	23.67	9	6
292	15.00	217.84	9	6
298	15.00	21.36	9	6
299	15.00	229.57	9	6
303	15.00	23.78	9	6
304	15.00	129.92	9	6
311	15.00	19.57	9	6
312	15.00	73.48	9	6
315	6.87	8.58	2	6
316	15.00	16.11	2	6
318	15.00	14.45	2	6
319	15.00	19.60	2	6
320	15.00	34.83	9	6
321	15.00	14.10	9	6
322	15.00	25.54	2	6
323	15.00	26.33	2	6
324	15.00	26.83	9	6
331	2.68	3.35	9	6
332	15.00	16.11	2	6
341	15.00	594.10	9	6
348	15.00	1209.63	9	6
351	15.00	854.33	9	6

Model zone number	Radius for the built-up area	Radius for the entire zone	Metro availability from Band Number	Other rail availability from Band Number
352	15.00	215.45	9	6
353	15.00	302.19	9	6
361	15.00	649.12	9	6
364	15.00	507.38	9	6
370	15.00	2248.71	9	6
371	15.00	1169.19	9	6
372	15.00	2630.10	9	6
373	15.00	2562.46	9	6
374	15.00	2537.97	9	6

Note: <
(1) In central urban zones, the radius of the built-up area may sometimes be smaller than that for the entire zone because large green spaces and historic monuments (such as the Forbidden City) are excluded from the built-up area;
(2) the minimum distance bands specified for metro and other rail may be longer than the actual distance bands available, in which case no metro/rail intrazonal links will be coded;
(3) the data above is used by a software program to code the intrazonal links, which are then verified by hand.>

Appendix 5 Scenario-test summary tables: short-term

Table A5.1. Summary by travel demand segment and mode: S01 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.0*	*485.5*	*45.2*	*14.6*	*1,992*	*21,952*	*0%*	*20%*	*2%*	*-2%*	*0%*	*0%*
	Car	11.8	797.9	42.1	16.8	1,009	11,871	-6%	33%	-2%	-5%	-10%	-16%
	Bus	5.7	100.6	42.3	8.1	378	2,162	5%	0%	2%	3%	10%	15%
	Walk	1.4	0.0	18.3	4.5	177	241	1%	-	1%	0%	5%	6%
	Cycle	2.7	0.0	26.6	6.0	67	179	2%	-	1%	1%	7%	8%
	Metro/rail	20.8	342.8	73.3	17.0	361	7,499	8%	4%	3%	5%	24%	34%
2	*All*	*9.1*	*264.9*	*44.2*	*12.4*	*6,524*	*59,555*	*0%*	*0%*	*3%*	*-4%*	*0%*	*0%*
	Car	7.1	460.3	38.1	11.1	2,542	17,937	-22%	14%	-5%	-18%	-22%	-39%
	Bus	6.4	100.6	43.5	8.8	1,717	10,927	7%	0%	3%	4%	19%	28%
	Walk	1.4	0.0	18.6	4.5	759	1,052	1%	-	1%	0%	11%	13%
	Cycle	2.6	0.0	26.1	5.9	330	853	2%	-	1%	1%	14%	16%
	Metro/rail	24.5	327.3	80.2	18.3	1,177	28,787	5%	6%	3%	2%	37%	44%
3	*All*	*8.4*	*159.6*	*43.4*	*11.7*	*2,749*	*23,223*	*1%*	*-7%*	*3%*	*-2%*	*0%*	*1%*
	Car	4.5	281.7	35.0	7.6	767	3,427	-29%	8%	-6%	-24%	-33%	-52%
	Bus	7.2	100.7	45.5	9.5	928	6,696	5%	0%	2%	3%	26%	32%
	Walk	1.4	0.0	19.1	4.5	432	620	2%	-	2%	0%	17%	20%
	Cycle	2.7	0.0	26.6	6.1	188	507	3%	-	2%	1%	22%	25%
	Metro/rail	27.7	297.9	85.4	19.4	433	11,972	-3%	4%	0%	-3%	25%	21%
4	*All*	*6.5*	*265.0*	*39.0*	*10.0*	*331*	*2,146*	*-1%*	*18%*	*1%*	*-1%*	*0%*	*-1%*
	Car	7.2	498.2	39.2	11.1	137	991	-7%	32%	-2%	-5%	-9%	-16%
	Bus	5.4	100.5	40.8	8.0	101	550	2%	0%	1%	2%	8%	10%
	Walk	1.3	0.0	18.1	4.5	45	61	1%	-	0%	0%	5%	5%
	Cycle	2.4	0.0	25.3	5.8	17	40	1%	-	0%	0%	5%	6%
	Metro/rail	16.6	299.5	71.3	13.9	30	503	11%	5%	3%	8%	16%	28%
5	*All*	*5.6*	*169.4*	*37.9*	*8.9*	*1,923*	*10,796*	*-1%*	*5%*	*1%*	*-2%*	*0%*	*-1%*
	Car	5.0	335.3	36.7	8.2	624	3,138	-16%	22%	-4%	-13%	-20%	-33%
	Bus	5.8	100.6	41.8	8.3	702	4,077	2%	0%	1%	2%	14%	17%
	Walk	1.4	0.0	18.4	4.5	303	417	1%	-	1%	0%	9%	10%
	Cycle	2.5	0.0	25.6	5.8	132	330	1%	-	1%	1%	10%	12%
	Metro/rail	17.6	284.3	72.6	14.5	161	2,834	9%	5%	3%	6%	26%	37%
6	*All*	*5.0*	*109.1*	*36.5*	*8.2*	*351*	*1,759*	*0%*	*-4%*	*0%*	*-1%*	*0%*	*0%*
	Car	3.5	225.8	34.3	6.1	78	274	-22%	16%	-5%	-18%	-33%	-47%
	Bus	6.3	100.6	43.1	8.8	150	949	0%	0%	0%	0%	17%	17%
	Walk	1.4	0.0	19.0	4.5	71	101	2%	-	2%	0%	13%	15%
	Cycle	2.6	0.0	26.1	6.0	31	80	2%	-	1%	1%	16%	17%
	Metro/rail	17.0	264.7	73.2	14.0	21	354	2%	4%	1%	1%	26%	28%
7	*All*	*34.2*	*1851.0*	*57.6*	*35.7*	*54*	*1,833*	*1%*	*39%*	*-2%*	*3%*	*0%*	*1%*
	Car	35.0	2168.9	58.4	35.9	36	1,246	-18%	24%	-9%	-10%	-5%	-22%
	Bus	5.7	100.6	43.1	8.0	5	30	4%	0%	1%	2%	5%	9%
	Walk	1.6	0.0	20.9	4.5	4	7	0%	-	0%	0%	2%	3%
	Cycle	3.1	0.0	29.3	6.4	1	4	1%	-	1%	0%	3%	4%
	Metro/rail	77.6	3010.3	92.4	50.4	7	546	139%	208%	24%	93%	23%	195%
8	*All*	*16.1*	*820.3*	*48.5*	*20.0*	*224*	*3,609*	*0%*	*27%*	*2%*	*-3%*	*0%*	*0%*
	Car	16.9	1105.1	46.1	22.0	152	2,576	-6%	35%	-2%	-4%	-7%	-13%
	Bus	6.9	100.7	45.6	9.1	22	151	12%	0%	4%	8%	14%	28%
	Walk	1.6	0.0	20.8	4.5	16	25	1%	-	1%	0%	7%	8%
	Cycle	2.8	0.0	27.5	6.1	5	13	2%	-	1%	1%	8%	10%
	Metro/rail	29.2	458.0	81.9	21.4	29	843	24%	14%	10%	13%	34%	65%
9	*All*	*12.4*	*522.2*	*46.9*	*15.8*	*65*	*806*	*-1%*	*12%*	*5%*	*-5%*	*0%*	*-1%*
	Car	11.4	734.1	42.0	16.3	40	459	-15%	24%	-4%	-11%	-14%	-27%
	Bus	8.9	100.9	49.3	10.9	8	75	27%	0%	9%	16%	33%	69%
	Walk	1.6	0.0	20.9	4.6	5	9	2%	-	1%	0%	15%	17%
	Cycle	2.8	0.0	27.3	6.1	1	4	4%	-	2%	2%	18%	22%
	Metro/rail	27.6	377.7	84.3	19.6	9	259	21%	10%	11%	10%	66%	102%
10	*All*	*10.9*	*369.1*	*44.2*	*14.8*	*2,026*	*22,141*	*0%*	*28%*	*2%*	*-2%*	*0%*	*0%*
	Car	14.0	750.5	43.3	19.5	772	10,842	-7%	49%	-2%	-5%	-12%	-19%
	Bus	6.0	100.6	42.6	8.5	535	3,235	5%	0%	2%	3%	7%	12%
	Walk	1.6	0.0	21.2	4.6	319	514	0%	-	0%	0%	4%	4%
	Cycle	2.6	0.0	26.4	6.0	83	218	1%	-	1%	1%	5%	6%
	Metro/rail	23.2	361.9	76.9	18.1	317	7,331	14%	6%	5%	8%	23%	40%
11	*All*	*10.3*	*245.7*	*44.4*	*13.9*	*10,042*	*103,289*	*0%*	*18%*	*5%*	*-5%*	*0%*	*0%*
	Car	11.3	512.4	40.9	16.6	3,181	35,974	-19%	47%	-6%	-14%	-26%	-40%
	Bus	6.9	100.7	44.5	9.3	2,977	20,594	12%	0%	4%	8%	16%	30%
	Walk	1.7	0.0	21.8	4.6	1,786	2,972	1%	-	1%	0%	8%	9%
	Cycle	2.6	0.0	26.4	6.0	519	1,369	2%	-	1%	1%	10%	12%
	Metro/rail	26.8	340.4	82.9	19.4	1,580	42,380	18%	10%	9%	8%	53%	81%
12	*All*	*8.4*	*149.9*	*42.8*	*11.8*	*2,159*	*18,089*	*0%*	*6%*	*7%*	*-7%*	*0%*	*0%*
	Car	7.6	310.9	37.5	12.1	520	3,947	-33%	35%	-9%	-26%	-43%	-62%
	Bus	7.9	100.8	47.0	10.1	717	5,696	18%	0%	7%	11%	28%	51%
	Walk	1.7	0.0	22.6	4.6	497	862	2%	-	2%	0%	15%	17%
	Cycle	2.7	0.0	26.8	6.1	135	367	4%	-	2%	2%	18%	23%
	Metro/rail	24.9	308.4	83.7	17.8	290	7,217	20%	14%	11%	9%	97%	137%

Table A5.2. Summary by travel demand segment and mode: S02 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.1*	*379.6*	*44.3*	*15.0*	*1,992*	*22,052*	*0%*	*-6%*	*0%*	*0%*	*0%*	*0%*
	Car	12.8	609.0	43.1	17.8	1,090	13,894	1%	1%	0%	1%	-3%	-2%
	Bus	5.4	0.0	41.5	7.8	389	2,111	-1%	-100%	0%	0%	13%	12%
	Walk	1.4	0.0	18.2	4.5	161	218	0%	-	0%	0%	-4%	-4%
	Cycle	2.6	0.0	26.4	6.0	60	159	0%	-	0%	0%	-4%	-4%
	Metro/rail	19.5	317.3	70.9	16.5	291	5,670	2%	-4%	0%	1%	0%	2%
2	*All*	*9.2*	*227.9*	*43.1*	*12.9*	*6,524*	*60,306*	*1%*	*-14%*	*1%*	*0%*	*0%*	*1%*
	Car	9.4	417.6	40.4	14.0	2,935	27,664	4%	3%	0%	3%	-10%	-6%
	Bus	5.9	0.0	42.2	8.3	1,861	10,896	-2%	-100%	-1%	-1%	29%	27%
	Walk	1.4	0.0	18.2	4.5	616	838	-1%	-	-1%	0%	-10%	-10%
	Cycle	2.5	0.0	25.8	5.9	260	658	0%	-	0%	0%	-11%	-11%
	Metro/rail	23.8	306.4	77.9	18.3	851	20,250	2%	-1%	0%	2%	-1%	1%
3	*All*	*8.7*	*123.3*	*43.4*	*12.0*	*2,749*	*23,791*	*3%*	*-28%*	*3%*	*0%*	*0%*	*3%*
	Car	6.8	276.2	37.4	10.8	881	5,957	7%	6%	0%	7%	-23%	-17%
	Bus	6.6	0.0	43.9	9.0	1,134	7,469	-4%	-100%	-2%	-3%	54%	47%
	Walk	1.4	0.0	18.5	4.5	288	397	-2%	-	-1%	0%	-22%	-23%
	Cycle	2.6	0.0	26.1	6.0	118	307	0%	-	0%	0%	-24%	-24%
	Metro/rail	29.4	290.5	85.9	20.5	329	9,661	3%	1%	0%	3%	-5%	-2%
4	*All*	*6.5*	*188.0*	*38.9*	*10.1*	*331*	*2,168*	*0%*	*-16%*	*0%*	*0%*	*0%*	*0%*
	Car	7.9	382.8	39.9	11.8	144	1,131	2%	1%	0%	2%	-5%	-4%
	Bus	5.3	0.0	40.4	7.8	105	555	-1%	-100%	0%	0%	12%	11%
	Walk	1.3	0.0	18.0	4.4	41	55	0%	-	0%	0%	-5%	-5%
	Cycle	2.4	0.0	25.1	5.7	15	36	0%	-	0%	0%	-5%	-5%
	Metro/rail	15.3	279.8	69.4	13.2	26	391	2%	-2%	0%	2%	-2%	0%
5	*All*	*5.8*	*115.5*	*38.1*	*9.1*	*1,923*	*11,079*	*2%*	*-28%*	*1%*	*1%*	*0%*	*2%*
	Car	6.1	280.1	38.0	9.7	676	4,147	3%	2%	0%	3%	-13%	-11%
	Bus	5.6	0.0	41.2	8.1	776	4,321	-2%	-100%	-1%	-1%	26%	24%
	Walk	1.3	0.0	18.1	4.5	247	332	-1%	-	-1%	0%	-12%	-12%
	Cycle	2.5	0.0	25.4	5.8	104	255	-1%	-	0%	0%	-13%	-13%
	Metro/rail	16.8	271.7	70.5	14.3	120	2,024	4%	0%	0%	4%	-6%	-2%
6	*All*	*5.4*	*58.0*	*37.9*	*8.5*	*351*	*1,880*	*7%*	*-49%*	*4%*	*3%*	*0%*	*7%*
	Car	4.6	199.4	35.9	7.7	83	384	3%	2%	-1%	4%	-29%	-26%
	Bus	6.0	0.0	42.3	8.6	187	1,129	-4%	-100%	-2%	-3%	46%	39%
	Walk	1.4	0.0	18.3	4.5	47	64	-2%	-	-2%	0%	-25%	-27%
	Cycle	2.5	0.0	25.7	5.9	19	49	-1%	-	-1%	-1%	-28%	-29%
	Metro/rail	17.7	261.2	72.6	14.6	14	254	6%	2%	0%	6%	-13%	-8%
7	*All*	*34.0*	*1322.1*	*58.9*	*34.6*	*54*	*1,817*	*0%*	*-1%*	*0%*	*0%*	*0%*	*0%*
	Car	42.9	1758.8	64.0	40.2	37	1,592	1%	1%	0%	0%	-1%	0%
	Bus	5.5	0.0	42.4	7.7	5	29	-1%	-100%	0%	0%	6%	5%
	Walk	1.6	0.0	20.8	4.5	4	7	0%	-	0%	0%	-1%	-1%
	Cycle	3.1	0.0	29.1	6.4	1	3	0%	-	0%	0%	-1%	-1%
	Metro/rail	32.5	958.6	74.6	26.2	6	186	0%	-2%	0%	0%	0%	0%
8	*All*	*16.2*	*629.1*	*47.4*	*20.5*	*224*	*3,616*	*0%*	*-2%*	*0%*	*0%*	*0%*	*0%*
	Car	18.2	821.8	47.2	23.1	161	2,929	1%	1%	0%	1%	-1%	-1%
	Bus	6.1	0.0	43.6	8.4	22	133	-1%	-100%	-1%	-1%	14%	13%
	Walk	1.6	0.0	20.6	4.5	15	23	0%	-	0%	0%	-2%	-2%
	Cycle	2.8	0.0	27.2	6.1	4	12	0%	-	0%	0%	-2%	-2%
	Metro/rail	23.8	388.9	74.8	19.1	22	518	1%	-3%	0%	1%	1%	2%
9	*All*	*12.5*	*445.8*	*45.0*	*16.7*	*65*	*814*	*0%*	*-4%*	*0%*	*0%*	*0%*	*0%*
	Car	13.6	597.1	44.0	18.5	45	615	1%	1%	0%	1%	-4%	-2%
	Bus	6.9	0.0	44.9	9.2	8	57	-2%	-100%	-1%	-1%	30%	28%
	Walk	1.6	0.0	20.6	4.5	5	7	0%	-	0%	0%	-4%	-4%
	Cycle	2.7	0.0	26.8	6.0	1	3	0%	-	0%	0%	-4%	-4%
	Metro/rail	23.2	336.5	76.2	18.3	6	132	2%	-2%	0%	2%	1%	3%
10	*All*	*11.0*	*256.5*	*43.3*	*15.2*	*2,026*	*22,216*	*0%*	*-11%*	*0%*	*0%*	*0%*	*0%*
	Car	15.4	514.6	44.5	20.8	847	13,080	2%	2%	0%	2%	-4%	-2%
	Bus	5.7	0.0	41.9	8.2	557	3,194	-1%	-100%	0%	0%	11%	11%
	Walk	1.6	0.0	21.1	4.6	292	467	0%	-	0%	0%	-5%	-5%
	Cycle	2.6	0.0	26.2	5.9	75	195	0%	-	0%	0%	-5%	-5%
	Metro/rail	20.7	328.0	73.1	17.0	255	5,280	2%	-4%	0%	1%	-1%	1%
11	*All*	*10.4*	*173.7*	*42.7*	*14.6*	*10,043*	*104,335*	*1%*	*-16%*	*1%*	*0%*	*0%*	*1%*
	Car	14.7	366.1	43.7	20.1	3,916	57,429	5%	5%	1%	5%	-9%	-4%
	Bus	6.1	0.0	42.6	8.6	3,246	19,731	-1%	-100%	-1%	-1%	26%	24%
	Walk	1.6	0.0	21.4	4.6	1,457	2,379	-1%	-	-1%	0%	-12%	-12%
	Cycle	2.6	0.0	26.1	5.9	414	1,069	0%	-	0%	0%	-12%	-12%
	Metro/rail	23.5	307.9	76.1	18.5	1,010	23,727	3%	0%	0%	3%	-2%	1%
12	*All*	*8.6*	*104.0*	*41.0*	*12.6*	*2,159*	*18,666*	*3%*	*-27%*	*3%*	*0%*	*0%*	*3%*
	Car	12.6	253.1	41.8	18.1	734	9,234	11%	10%	1%	10%	-19%	-10%
	Bus	6.5	0.0	43.5	8.9	866	5,615	-3%	-100%	-1%	-2%	54%	49%
	Walk	1.7	0.0	21.9	4.6	333	557	-2%	-	-2%	0%	-23%	-24%
	Cycle	2.6	0.0	26.2	6.0	86	226	0%	-	0%	0%	-24%	-24%
	Metro/rail	21.6	276.2	75.8	17.1	140	3,034	4%	2%	0%	4%	-5%	0%

Table A5.3. Summary by travel demand segment and mode: S03 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.0*	*498.7*	*42.5*	*15.5*	*1,992*	*21,889*	*-1%*	*23%*	*-4%*	*3%*	*0%*	*-1%*
	Car	13.5	644.9	43.7	18.5	1,236	16,646	7%	7%	2%	5%	10%	18%
	Bus	5.6	100.6	42.1	8.0	355	1,997	3%	0%	1%	2%	3%	6%
	Walk	1.4	0.0	18.3	4.5	170	232	1%	-	0%	0%	1%	2%
	Cycle	2.7	0.0	26.7	6.0	64	172	2%	-	1%	1%	2%	4%
	Metro/rail	17.2	967.1	65.6	15.7	166	2,842	-11%	192%	-7%	-3%	-43%	-49%
2	*All*	*9.1*	*353.5*	*40.2*	*13.7*	*6,524*	*59,670*	*0%*	*33%*	*-6%*	*6%*	*0%*	*0%*
	Car	11.6	511.9	42.2	16.5	3,776	43,814	28%	26%	5%	22%	16%	48%
	Bus	6.5	100.7	44.0	8.9	1,518	9,915	10%	0%	4%	6%	5%	16%
	Walk	1.4	0.0	18.5	4.5	695	958	1%	-	1%	0%	2%	3%
	Cycle	2.6	0.0	26.1	5.9	298	773	2%	-	1%	1%	3%	5%
	Metro/rail	17.8	934.8	65.3	16.4	236	4,210	-23%	202%	-16%	-8%	-73%	-79%
3	*All*	*8.4*	*220.9*	*40.8*	*12.3*	*2,749*	*23,028*	*0%*	*29%*	*-3%*	*3%*	*0%*	*0%*
	Car	9.3	373.7	39.7	14.0	1,330	12,343	47%	43%	6%	39%	16%	72%
	Bus	10.7	101.1	54.0	11.9	861	9,245	56%	0%	21%	29%	17%	82%
	Walk	1.4	0.0	18.8	4.5	373	527	1%	-	1%	0%	1%	2%
	Cycle	2.7	0.0	26.6	6.1	159	428	3%	-	2%	1%	3%	6%
	Metro/rail	18.4	883.3	63.5	17.4	26	486	-35%	208%	-26%	-13%	-92%	-95%
4	*All*	*6.4*	*260.0*	*37.8*	*10.2*	*331*	*2,131*	*-1%*	*16%*	*-3%*	*1%*	*0%*	*-1%*
	Car	8.3	402.4	40.2	12.3	160	1,322	7%	6%	1%	6%	5%	13%
	Bus	5.3	100.5	40.6	7.9	96	515	1%	0%	1%	0%	3%	3%
	Walk	1.3	0.0	18.1	4.4	44	59	0%	-	0%	0%	2%	2%
	Cycle	2.4	0.0	25.2	5.7	16	39	1%	-	0%	0%	2%	3%
	Metro/rail	13.0	808.7	64.6	12.1	15	196	-13%	183%	-7%	-7%	-43%	-50%
5	*All*	*5.6*	*185.4*	*36.4*	*9.2*	*1,923*	*10,702*	*-2%*	*15%*	*-3%*	*2%*	*0%*	*-2%*
	Car	6.9	314.1	38.7	10.8	839	5,828	16%	14%	2%	14%	8%	25%
	Bus	5.8	100.6	41.8	8.4	638	3,722	3%	0%	1%	2%	3%	6%
	Walk	1.4	0.0	18.3	4.5	284	388	0%	-	0%	0%	2%	2%
	Cycle	2.5	0.0	25.6	5.8	122	305	1%	-	1%	1%	2%	4%
	Metro/rail	12.0	748.2	60.7	11.9	38	460	-26%	176%	-14%	-14%	-70%	-78%
6	*All*	*4.9*	*122.0*	*35.5*	*8.3*	*351*	*1,731*	*-2%*	*7%*	*-3%*	*1%*	*0%*	*-2%*
	Car	5.3	226.3	36.6	8.7	125	662	19%	16%	2%	17%	7%	27%
	Bus	6.7	100.7	44.0	9.1	134	890	6%	0%	2%	3%	4%	10%
	Walk	1.4	0.0	18.8	4.5	64	90	0%	-	0%	0%	1%	2%
	Cycle	2.6	0.0	26.1	6.0	27	71	1%	-	1%	1%	2%	4%
	Metro/rail	10.8	680.3	56.7	11.4	2	18	-35%	167%	-22%	-17%	-90%	-94%
7	*All*	*33.9*	*1406.7*	*58.2*	*34.9*	*54*	*1,815*	*0%*	*5%*	*-1%*	*1%*	*0%*	*0%*
	Car	42.4	1743.1	63.7	39.9	38	1,622	-1%	0%	0%	0%	2%	2%
	Bus	5.6	100.6	42.8	7.8	5	29	1%	0%	1%	1%	1%	3%
	Walk	1.6	0.0	20.9	4.5	4	7	0%	-	0%	0%	1%	1%
	Cycle	3.1	0.0	29.3	6.4	1	3	1%	-	1%	1%	1%	2%
	Metro/rail	32.7	1719.9	71.8	27.4	5	153	1%	76%	-4%	5%	-18%	-17%
8	*All*	*16.1*	*714.6*	*46.0*	*21.0*	*224*	*3,600*	*0%*	*11%*	*-3%*	*2%*	*0%*	*0%*
	Car	18.6	841.5	47.4	23.5	172	3,198	3%	3%	1%	2%	5%	8%
	Bus	6.3	100.6	44.3	8.5	20	124	2%	0%	1%	1%	3%	5%
	Walk	1.6	0.0	20.7	4.5	15	24	1%	-	1%	0%	1%	2%
	Cycle	2.8	0.0	27.4	6.1	4	13	2%	-	1%	1%	2%	4%
	Metro/rail	19.6	1068.6	67.1	17.6	12	242	-17%	165%	-10%	-7%	-43%	-53%
9	*All*	*12.4*	*524.3*	*43.0*	*17.4*	*65*	*809*	*0%*	*12%*	*-4%*	*4%*	*0%*	*0%*
	Car	14.2	628.5	44.4	19.2	51	721	7%	7%	1%	5%	8%	15%
	Bus	7.4	100.7	46.2	9.6	7	48	5%	0%	2%	3%	4%	9%
	Walk	1.6	0.0	20.7	4.5	5	8	1%	-	1%	0%	1%	2%
	Cycle	2.8	0.0	27.1	6.1	1	3	3%	-	1%	1%	2%	5%
	Metro/rail	16.4	922.1	63.0	15.6	2	28	-28%	169%	-17%	-13%	-70%	-78%
10	*All*	*10.8*	*353.8*	*41.5*	*15.7*	*2,026*	*21,952*	*-1%*	*23%*	*-4%*	*3%*	*0%*	*-1%*
	Car	16.2	541.4	45.1	21.6	973	15,770	7%	7%	2%	6%	10%	18%
	Bus	5.9	100.6	42.3	8.3	516	3,030	2%	0%	1%	1%	3%	5%
	Walk	1.6	0.0	21.2	4.6	312	503	0%	-	0%	0%	2%	2%
	Cycle	2.6	0.0	26.4	6.0	81	214	2%	-	1%	1%	2%	4%
	Metro/rail	16.9	960.8	66.1	15.3	144	2,433	-17%	181%	-9%	-8%	-44%	-54%
11	*All*	*10.2*	*243.4*	*40.0*	*15.3*	*10,042*	*102,638*	*-1%*	*17%*	*-5%*	*5%*	*0%*	*-1%*
	Car	15.8	397.0	44.6	21.2	4,950	78,113	13%	14%	3%	10%	15%	30%
	Bus	6.3	100.6	43.4	8.8	2,671	16,924	3%	0%	1%	1%	4%	7%
	Walk	1.7	0.0	21.7	4.6	1,679	2,779	0%	-	0%	0%	2%	2%
	Cycle	2.6	0.0	26.4	6.0	485	1,277	2%	-	1%	1%	3%	5%
	Metro/rail	13.7	816.1	60.6	13.6	258	3,544	-40%	164%	-20%	-24%	-75%	-85%
12	*All*	*8.4*	*152.3*	*38.1*	*13.2*	*2,159*	*18,074*	*0%*	*8%*	*-4%*	*4%*	*0%*	*0%*
	Car	12.7	258.8	42.3	18.0	1,019	12,911	12%	12%	2%	9%	12%	26%
	Bus	6.9	100.7	44.7	9.3	578	4,000	3%	0%	1%	2%	3%	6%
	Walk	1.7	0.0	22.3	4.6	436	746	0%	-	0%	0%	1%	2%
	Cycle	2.7	0.0	26.5	6.0	116	310	2%	-	1%	1%	2%	4%
	Metro/rail	10.2	661.5	54.2	11.2	10	106	-51%	145%	-28%	-31%	-93%	-97%

Table A5.4. Summary by travel demand segment and mode: S04 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	All	11.1	390.8	45.3	14.6	1,992	22,019	0%	-4%	3%	-2%	0%	0%
	Car	13.0	616.6	44.9	17.4	1,026	13,330	3%	3%	4%	-1%	-9%	-6%
	Bus	5.4	100.5	41.5	7.8	388	2,102	-1%	0%	0%	0%	13%	12%
	Walk	1.4	0.0	18.4	4.5	185	253	1%	-	1%	0%	10%	11%
	Cycle	2.6	0.0	26.4	6.0	70	185	0%	-	0%	0%	11%	12%
	Metro/rail	19.0	330.2	70.8	16.1	323	6,150	-1%	0%	0%	-1%	11%	10%
2	All	9.2	254.1	43.4	12.7	6,524	59,807	0%	-4%	2%	-2%	0%	0%
	Car	9.3	410.9	41.5	13.4	2,947	27,394	2%	1%	3%	-1%	-9%	-7%
	Bus	5.9	100.6	42.2	8.3	1,587	9,326	-1%	0%	0%	-1%	10%	9%
	Walk	1.4	0.0	18.5	4.5	742	1,023	1%	-	1%	0%	9%	10%
	Cycle	2.5	0.0	25.9	5.9	319	813	0%	-	0%	0%	10%	10%
	Metro/rail	22.9	309.4	77.6	17.7	928	21,251	-1%	0%	0%	-1%	8%	6%
3	All	8.4	167.6	42.5	11.8	2,749	23,087	0%	-2%	1%	-1%	0%	0%
	Car	6.3	260.8	37.9	10.0	1,078	6,816	0%	0%	1%	-1%	-6%	-5%
	Bus	6.8	100.7	44.4	9.2	768	5,236	-1%	0%	0%	-1%	4%	3%
	Walk	1.4	0.0	18.8	4.5	383	539	0%	-	0%	0%	4%	5%
	Cycle	2.6	0.0	26.2	6.0	162	425	0%	-	0%	0%	5%	5%
	Metro/rail	28.2	286.1	85.3	19.8	357	10,071	-1%	0%	-1%	-1%	3%	2%
4	All	6.5	217.5	39.2	10.0	331	2,160	0%	-3%	1%	-1%	0%	0%
	Car	8.0	386.5	40.8	11.7	139	1,108	3%	2%	2%	0%	-8%	-6%
	Bus	5.3	100.5	40.4	7.8	101	529	-1%	0%	0%	-1%	7%	6%
	Walk	1.3	0.0	18.1	4.5	46	62	1%	-	1%	0%	6%	7%
	Cycle	2.4	0.0	25.2	5.7	17	41	1%	-	0%	0%	7%	7%
	Metro/rail	14.8	283.8	69.1	12.8	28	420	-1%	-1%	0%	-1%	8%	7%
5	All	5.7	157.5	37.8	9.0	1,923	10,887	0%	-2%	0%	0%	0%	0%
	Car	6.0	276.9	38.6	9.4	728	4,401	1%	1%	1%	0%	-7%	-5%
	Bus	5.6	100.6	41.3	8.2	645	3,630	-1%	0%	0%	0%	4%	4%
	Walk	1.4	0.0	18.3	4.5	290	396	0%	-	0%	0%	4%	4%
	Cycle	2.5	0.0	25.5	5.8	125	309	0%	-	0%	0%	5%	5%
	Metro/rail	15.9	269.5	70.2	13.6	135	2,151	-1%	0%	0%	-1%	6%	4%
6	All	5.0	111.7	36.5	8.2	351	1,763	0%	-2%	0%	0%	0%	0%
	Car	4.5	195.6	36.3	7.4	111	497	0%	0%	1%	0%	-5%	-5%
	Bus	6.3	100.6	42.9	8.8	132	824	-1%	0%	0%	0%	2%	2%
	Walk	1.4	0.0	18.8	4.5	64	91	0%	-	0%	0%	2%	3%
	Cycle	2.6	0.0	25.9	5.9	27	70	0%	-	0%	0%	3%	3%
	Metro/rail	16.5	254.1	72.5	13.7	17	282	-1%	0%	0%	-1%	3%	2%
7	All	34.0	1328.1	61.2	33.3	54	1,817	0%	-1%	4%	-4%	0%	0%
	Car	44.3	1814.3	68.5	38.8	36	1,579	4%	4%	7%	-3%	-5%	-1%
	Bus	5.4	100.5	42.2	7.7	6	31	-1%	0%	-1%	-1%	14%	12%
	Walk	1.6	0.0	20.8	4.5	5	7	0%	-	0%	0%	11%	11%
	Cycle	3.1	0.0	28.9	6.4	1	4	-1%	-	0%	0%	11%	10%
	Metro/rail	31.7	952.8	74.3	25.6	6	196	-2%	-2%	0%	-2%	8%	6%
8	All	16.2	635.3	49.4	19.6	224	3,614	0%	-1%	4%	-4%	0%	0%
	Car	18.5	834.8	50.2	22.1	156	2,898	3%	2%	7%	-4%	-4%	-2%
	Bus	6.0	100.6	43.4	8.3	22	132	-2%	0%	-1%	-1%	14%	12%
	Walk	1.6	0.0	20.7	4.5	17	27	1%	-	1%	0%	12%	13%
	Cycle	2.7	0.0	27.1	6.1	5	14	0%	-	0%	0%	13%	12%
	Metro/rail	23.1	397.3	74.3	18.7	24	544	-2%	-1%	-1%	-2%	9%	7%
9	All	12.5	459.6	46.2	16.2	65	812	0%	-1%	3%	-3%	0%	0%
	Car	13.6	598.3	46.0	17.7	45	616	2%	1%	5%	-3%	-4%	-2%
	Bus	6.9	100.7	44.9	9.2	7	48	-2%	0%	-1%	-2%	11%	8%
	Walk	1.6	0.0	20.8	4.5	5	8	1%	-	1%	0%	10%	11%
	Cycle	2.7	0.0	26.8	6.0	1	4	0%	-	0%	0%	11%	11%
	Metro/rail	22.3	339.3	75.6	17.7	6	136	-2%	-1%	-1%	-1%	8%	6%
10	All	10.9	282.1	43.7	15.0	2,026	22,166	0%	-2%	1%	-1%	0%	0%
	Car	15.7	520.4	45.5	20.7	817	12,812	4%	3%	3%	1%	-7%	-4%
	Bus	5.7	100.6	42.0	8.2	527	3,030	0%	0%	0%	0%	5%	5%
	Walk	1.6	0.0	21.2	4.6	321	519	1%	-	0%	0%	5%	5%
	Cycle	2.6	0.0	26.3	5.9	84	218	1%	-	0%	0%	5%	6%
	Metro/rail	20.1	337.6	72.7	16.6	277	5,588	-1%	-1%	0%	-1%	8%	6%
11	All	10.3	204.3	42.6	14.5	10,042	103,380	0%	-2%	1%	-1%	0%	0%
	Car	14.5	360.4	44.4	19.5	3,976	57,477	4%	3%	2%	1%	-8%	-4%
	Bus	6.1	100.6	42.8	8.6	2,718	16,662	-1%	0%	0%	0%	6%	5%
	Walk	1.7	0.0	21.7	4.6	1,728	2,865	1%	-	1%	0%	5%	6%
	Cycle	2.6	0.0	26.2	6.0	498	1,295	1%	-	0%	0%	6%	6%
	Metro/rail	22.3	307.4	75.4	17.8	1,122	25,080	-2%	-1%	-1%	-1%	9%	7%
12	All	8.4	140.1	40.0	12.6	2,159	18,103	0%	-1%	1%	-1%	0%	0%
	Car	11.5	233.3	41.8	16.5	865	9,942	2%	1%	1%	0%	-5%	-3%
	Bus	6.7	100.7	44.0	9.1	577	3,864	0%	0%	0%	0%	3%	3%
	Walk	1.7	0.0	22.3	4.6	442	756	0%	-	0%	0%	3%	3%
	Cycle	2.6	0.0	26.3	6.0	117	309	0%	-	0%	0%	3%	3%
	Metro/rail	20.4	269.4	75.2	16.3	159	3,233	-1%	0%	-1%	-1%	8%	6%

Table A5.5. Summary by travel demand segment and mode: S05 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.1*	*378.4*	*41.4*	*16.0*	*1,992*	*22,035*	*0%*	*-7%*	*-6%*	*7%*	*0%*	*0%*
	Car	14.4	682.0	44.1	19.7	874	12,626	15%	13%	3%	12%	-22%	-11%
	Bus	5.7	100.6	31.8	10.7	698	3,966	4%	0%	-24%	36%	103%	111%
	Walk	1.3	0.0	17.9	4.5	119	158	-2%	-	-2%	0%	-29%	-30%
	Cycle	2.7	0.0	26.7	6.0	44	117	2%	-	1%	1%	-30%	-29%
	Metro/rail	20.1	339.3	71.7	16.8	257	5,167	5%	2%	1%	4%	-12%	-7%
2	*All*	*9.3*	*240.0*	*39.5*	*14.1*	*6,524*	*60,768*	*2%*	*-9%*	*-8%*	*10%*	*0%*	*2%*
	Car	10.7	466.3	41.1	15.6	2,226	23,794	17%	15%	2%	15%	-32%	-20%
	Bus	6.1	100.6	32.5	11.2	2,912	17,679	2%	0%	-23%	33%	102%	106%
	Walk	1.3	0.0	17.9	4.5	455	608	-2%	-	-2%	0%	-33%	-35%
	Cycle	2.5	0.0	25.8	5.9	187	473	0%	-	0%	0%	-36%	-36%
	Metro/rail	24.5	315.1	79.1	18.6	744	18,215	5%	2%	2%	4%	-14%	-9%
3	*All*	*8.8*	*154.8*	*39.1*	*13.5*	*2,749*	*24,130*	*5%*	*-10%*	*-8%*	*13%*	*0%*	*5%*
	Car	7.1	285.8	37.5	11.3	688	4,878	13%	10%	0%	12%	-40%	-32%
	Bus	6.9	100.7	34.4	12.1	1,454	10,059	1%	0%	-23%	30%	97%	98%
	Walk	1.4	0.0	18.2	4.5	229	310	-3%	-	-3%	0%	-38%	-40%
	Cycle	2.6	0.0	26.0	5.9	91	236	-1%	-	-1%	-1%	-41%	-42%
	Metro/rail	30.1	286.9	87.1	20.7	287	8,647	5%	0%	2%	4%	-17%	-13%
4	*All*	*6.6*	*201.3*	*34.5*	*11.6*	*331*	*2,201*	*2%*	*-10%*	*-11%*	*15%*	*0%*	*2%*
	Car	9.0	430.8	40.3	13.4	100	908	17%	14%	1%	16%	-34%	-23%
	Bus	5.2	100.5	30.2	10.4	171	893	-2%	0%	-25%	32%	82%	79%
	Walk	1.3	0.0	17.6	4.4	29	38	-3%	-	-2%	0%	-33%	-35%
	Cycle	2.4	0.0	25.0	5.7	10	24	-1%	-	-1%	-1%	-36%	-36%
	Metro/rail	16.6	303.0	70.2	14.2	20	338	11%	6%	1%	10%	-22%	-14%
5	*All*	*5.9*	*145.7*	*33.3*	*10.7*	*1,923*	*11,413*	*5%*	*-10%*	*-12%*	*19%*	*0%*	*5%*
	Car	6.8	303.1	38.2	10.7	463	3,140	14%	10%	0%	13%	-41%	-32%
	Bus	5.5	100.5	30.9	10.7	1,118	6,139	-3%	0%	-25%	30%	81%	75%
	Walk	1.3	0.0	17.7	4.4	174	228	-4%	-	-3%	0%	-38%	-40%
	Cycle	2.4	0.0	25.2	5.8	71	171	-2%	-	-1%	-1%	-41%	-42%
	Metro/rail	18.0	284.4	71.4	15.1	96	1,735	12%	5%	1%	10%	-25%	-16%
6	*All*	*5.5*	*109.3*	*32.4*	*10.2*	*351*	*1,944*	*10%*	*-4%*	*-11%*	*24%*	*0%*	*10%*
	Car	4.7	202.2	35.8	7.9	62	293	6%	4%	-1%	7%	-47%	-44%
	Bus	6.0	100.6	32.1	11.2	227	1,354	-5%	0%	-25%	27%	76%	67%
	Walk	1.3	0.0	18.0	4.5	36	49	-4%	-	-4%	-1%	-42%	-45%
	Cycle	2.5	0.0	25.5	5.9	14	36	-3%	-	-1%	-1%	-46%	-47%
	Metro/rail	18.1	259.7	73.3	14.8	12	212	8%	2%	1%	7%	-29%	-23%
7	*All*	*33.9*	*1319.2*	*57.3*	*35.5*	*54*	*1,815*	*0%*	*-1%*	*-3%*	*3%*	*0%*	*0%*
	Car	46.8	1908.8	66.7	42.0	34	1,570	10%	9%	4%	5%	-10%	-1%
	Bus	5.5	100.5	31.5	10.4	10	55	-1%	0%	-26%	34%	98%	97%
	Walk	1.6	0.0	20.8	4.5	4	6	0%	-	0%	0%	-16%	-15%
	Cycle	3.2	0.0	29.6	6.5	1	3	3%	-	2%	1%	-15%	-12%
	Metro/rail	33.9	1025.6	75.4	27.0	5	181	4%	5%	1%	3%	-7%	-2%
8	*All*	*16.1*	*622.3*	*45.8*	*21.1*	*224*	*3,609*	*0%*	*-3%*	*-3%*	*3%*	*0%*	*0%*
	Car	19.5	874.2	48.0	24.3	145	2,821	8%	7%	2%	6%	-11%	-4%
	Bus	6.3	100.6	33.3	11.3	42	266	2%	0%	-24%	34%	120%	125%
	Walk	1.6	0.0	20.6	4.5	13	20	0%	-	0%	0%	-17%	-17%
	Cycle	2.8	0.0	27.4	6.1	4	10	2%	-	1%	1%	-16%	-15%
	Metro/rail	24.3	411.2	75.5	19.3	20	491	3%	2%	1%	2%	-6%	-4%
9	*All*	*12.5*	*436.8*	*43.2*	*17.4*	*65*	*814*	*0%*	*-6%*	*-4%*	*4%*	*0%*	*0%*
	Car	14.4	629.9	44.4	19.5	40	574	8%	7%	1%	7%	-15%	-9%
	Bus	7.3	100.7	35.1	12.4	15	110	3%	0%	-22%	33%	139%	146%
	Walk	1.5	0.0	20.5	4.5	4	6	-1%	-	-1%	0%	-19%	-19%
	Cycle	2.7	0.0	26.9	6.1	1	3	1%	-	1%	0%	-19%	-18%
	Metro/rail	23.2	346.7	76.7	18.2	5	121	2%	1%	1%	2%	-8%	-6%
10	*All*	*11.0*	*275.6*	*39.8*	*16.7*	*2,026*	*22,379*	*1%*	*-4%*	*-8%*	*10%*	*0%*	*1%*
	Car	18.1	594.0	45.9	23.7	658	11,902	20%	18%	4%	16%	-25%	-11%
	Bus	5.8	100.6	31.9	11.0	898	5,237	1%	0%	-24%	33%	80%	82%
	Walk	1.6	0.0	20.6	4.5	201	314	-3%	-	-2%	0%	-34%	-36%
	Cycle	2.6	0.0	26.3	6.0	51	134	1%	-	0%	0%	-36%	-35%
	Metro/rail	21.9	354.2	74.2	17.8	218	4,792	8%	4%	2%	6%	-15%	-9%
11	*All*	*10.5*	*202.8*	*39.0*	*16.2*	*10,042*	*105,629*	*2%*	*-2%*	*-8%*	*11%*	*0%*	*2%*
	Car	17.0	416.8	44.9	22.7	3,060	51,926	22%	19%	3%	18%	-29%	-14%
	Bus	6.2	100.6	32.8	11.4	4,795	29,813	1%	0%	-24%	32%	86%	88%
	Walk	1.6	0.0	21.0	4.6	1,027	1,637	-3%	-	-3%	0%	-38%	-40%
	Cycle	2.6	0.0	26.1	5.9	287	739	0%	-	0%	0%	-39%	-39%
	Metro/rail	24.7	319.1	77.5	19.1	873	21,513	8%	3%	2%	6%	-15%	-8%
12	*All*	*8.8*	*143.1*	*36.9*	*14.3*	*2,159*	*18,955*	*5%*	*1%*	*-7%*	*13%*	*0%*	*5%*
	Car	13.7	272.0	42.4	19.4	604	8,290	21%	18%	2%	18%	-33%	-19%
	Bus	6.7	100.7	33.8	11.9	1,103	7,373	0%	0%	-23%	30%	97%	96%
	Walk	1.6	0.0	21.5	4.6	262	431	-4%	-	-3%	0%	-39%	-41%
	Cycle	2.6	0.0	26.1	6.0	67	174	-1%	-	-1%	0%	-41%	-42%
	Metro/rail	21.9	273.8	76.7	17.1	123	2,687	6%	1%	1%	4%	-17%	-12%

Table A5.6. Summary by travel demand segment and mode: S06 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.1*	*342.7*	*41.1*	*16.2*	*1,992*	*22,072*	*0%*	*-16%*	*-7%*	*8%*	*0%*	*0%*
	Car	13.8	647.7	43.6	19.0	761	10,507	10%	8%	2%	8%	-32%	-26%
	Bus	5.5	100.5	31.2	10.6	652	3,583	1%	0%	-25%	34%	90%	91%
	Walk	1.3	0.0	17.6	4.4	114	150	-4%	-	-3%	0%	-32%	-34%
	Cycle	2.6	0.0	26.0	5.9	41	106	-2%	-	-1%	-1%	-35%	-36%
	Metro/rail	18.3	293.0	59.4	18.5	422	7,727	-5%	-11%	-16%	14%	45%	39%
2	*All*	*9.4*	*219.6*	*39.2*	*14.3*	*6,524*	*61,074*	*2%*	*-17%*	*-8%*	*11%*	*0%*	*2%*
	Car	9.6	420.3	40.3	14.3	1,970	18,967	6%	4%	0%	6%	-39%	-36%
	Bus	5.8	100.6	31.8	11.0	2,761	16,092	-2%	0%	-25%	31%	92%	88%
	Walk	1.3	0.0	17.7	4.5	442	581	-4%	-	-3%	-1%	-35%	-38%
	Cycle	2.5	0.0	25.4	5.8	179	441	-3%	-	-2%	-1%	-38%	-40%
	Metro/rail	21.3	278.9	65.1	19.6	1,173	24,993	-8%	-10%	-16%	10%	36%	25%
3	*All*	*8.9*	*152.0*	*38.3*	*13.9*	*2,749*	*24,358*	*6%*	*-11%*	*-10%*	*17%*	*0%*	*6%*
	Car	6.4	259.4	37.1	10.3	636	4,060	1%	-1%	-1%	2%	-44%	-44%
	Bus	6.5	100.6	33.3	11.7	1,387	9,012	-6%	0%	-25%	26%	88%	78%
	Walk	1.3	0.0	18.0	4.5	224	301	-4%	-	-4%	-1%	-39%	-42%
	Cycle	2.5	0.0	25.7	5.9	89	225	-3%	-	-2%	-2%	-43%	-44%
	Metro/rail	26.1	274.8	70.5	22.2	412	10,760	-9%	-4%	-18%	11%	19%	9%
4	*All*	*6.8*	*194.6*	*34.9*	*11.6*	*331*	*2,235*	*4%*	*-13%*	*-10%*	*15%*	*0%*	*4%*
	Car	8.6	411.7	40.1	12.9	93	799	12%	9%	1%	11%	-39%	-32%
	Bus	5.2	100.5	30.1	10.3	163	844	-2%	0%	-26%	32%	74%	70%
	Walk	1.3	0.0	17.4	4.4	28	36	-4%	-	-3%	0%	-36%	-38%
	Cycle	2.3	0.0	24.8	5.6	10	23	-3%	-	-1%	-1%	-38%	-40%
	Metro/rail	14.1	262.7	58.4	14.5	38	533	-6%	-8%	-16%	12%	44%	36%
5	*All*	*6.0*	*142.8*	*33.5*	*10.8*	*1,923*	*11,592*	*6%*	*-12%*	*-11%*	*20%*	*0%*	*6%*
	Car	6.3	281.5	37.9	9.9	429	2,682	5%	3%	-1%	5%	-45%	-42%
	Bus	5.4	100.5	30.7	10.6	1,075	5,840	-4%	0%	-26%	29%	74%	67%
	Walk	1.3	0.0	17.5	4.4	169	220	-4%	-	-4%	-1%	-39%	-42%
	Cycle	2.4	0.0	25.0	5.7	68	163	-3%	-	-2%	-2%	-43%	-45%
	Metro/rail	14.9	253.0	58.4	15.3	181	2,688	-8%	-7%	-17%	11%	41%	30%
6	*All*	*5.6*	*110.1*	*32.5*	*10.4*	*351*	*1,972*	*12%*	*-3%*	*-11%*	*25%*	*0%*	*12%*
	Car	4.4	188.8	35.6	7.3	59	257	-2%	-3%	-1%	-1%	-49%	-51%
	Bus	5.9	100.6	31.9	11.1	221	1,301	-6%	0%	-26%	26%	72%	61%
	Walk	1.3	0.0	17.9	4.5	36	48	-5%	-	-4%	-1%	-43%	-46%
	Cycle	2.5	0.0	25.4	5.8	14	35	-4%	-	-2%	-2%	-47%	-49%
	Metro/rail	15.2	244.8	59.3	15.4	22	332	-9%	-4%	-19%	12%	32%	20%
7	*All*	*34.0*	*1297.1*	*56.9*	*35.8*	*54*	*1,817*	*0%*	*-3%*	*-3%*	*3%*	*0%*	*0%*
	Car	48.3	1964.3	67.9	42.7	32	1,537	13%	12%	6%	7%	-15%	-4%
	Bus	5.4	100.5	31.2	10.4	10	51	-2%	0%	-27%	33%	89%	85%
	Walk	1.5	0.0	20.5	4.5	4	5	-2%	-	-1%	0%	-18%	-19%
	Cycle	3.1	0.0	29.0	6.4	1	3	-1%	-	0%	0%	-19%	-20%
	Metro/rail	28.5	770.9	63.4	26.9	8	221	-12%	-21%	-15%	3%	36%	19%
8	*All*	*16.2*	*593.1*	*45.7*	*21.2*	*224*	*3,616*	*0%*	*-8%*	*-3%*	*4%*	*0%*	*0%*
	Car	19.4	867.3	48.0	24.2	136	2,627	7%	6%	2%	5%	-17%	-11%
	Bus	6.2	100.6	32.9	11.2	40	250	0%	0%	-25%	33%	111%	111%
	Walk	1.5	0.0	20.3	4.5	12	19	-2%	-	-2%	0%	-19%	-20%
	Cycle	2.7	0.0	26.9	6.0	4	9	-2%	-	-1%	-1%	-20%	-21%
	Metro/rail	22.3	345.8	63.8	21.0	32	711	-6%	-14%	-15%	11%	48%	39%
9	*All*	*12.6*	*410.9*	*43.1*	*17.5*	*65*	*816*	*0%*	*-12%*	*-4%*	*4%*	*0%*	*0%*
	Car	14.0	609.9	44.2	19.0	37	518	5%	3%	1%	4%	-21%	-18%
	Bus	7.1	100.7	34.6	12.3	15	103	1%	0%	-24%	32%	129%	130%
	Walk	1.5	0.0	20.3	4.5	4	6	-2%	-	-2%	0%	-20%	-22%
	Cycle	2.6	0.0	26.4	6.0	1	2	-2%	-	-1%	-1%	-22%	-24%
	Metro/rail	21.4	307.8	64.5	19.9	9	187	-6%	-10%	-15%	11%	55%	46%
10	*All*	*11.1*	*261.7*	*39.9*	*16.7*	*2,026*	*22,538*	*2%*	*-9%*	*-8%*	*10%*	*0%*	*2%*
	Car	17.7	580.3	45.7	23.3	580	10,283	18%	15%	3%	14%	-34%	-23%
	Bus	5.7	100.6	31.6	10.9	847	4,860	-1%	0%	-25%	32%	70%	68%
	Walk	1.5	0.0	20.4	4.5	194	298	-4%	-	-3%	0%	-37%	-39%
	Cycle	2.5	0.0	25.8	5.9	48	122	-2%	-	-1%	-1%	-39%	-41%
	Metro/rail	19.5	304.0	62.4	18.7	357	6,974	-4%	-11%	-14%	12%	39%	33%
11	*All*	*10.6*	*195.4*	*39.1*	*16.3*	*10,043*	*106,356*	*3%*	*-6%*	*-7%*	*11%*	*0%*	*3%*
	Car	16.3	398.6	44.5	21.9	2,682	43,670	17%	14%	3%	14%	-38%	-27%
	Bus	6.1	100.6	32.4	11.3	4,583	27,968	-1%	0%	-24%	31%	78%	76%
	Walk	1.6	0.0	20.8	4.6	999	1,578	-4%	-	-4%	-1%	-39%	-42%
	Cycle	2.5	0.0	25.7	5.9	275	689	-3%	-	-2%	-1%	-42%	-43%
	Metro/rail	21.6	287.6	64.2	20.2	1,503	32,451	-5%	-7%	-16%	12%	46%	38%
12	*All*	*8.8*	*141.7*	*37.0*	*14.3*	*2,159*	*19,087*	*5%*	*0%*	*-7%*	*13%*	*0%*	*5%*
	Car	12.9	255.8	41.9	18.5	539	6,971	14%	11%	1%	13%	-41%	-32%
	Bus	6.5	100.7	33.4	11.8	1,069	6,998	-2%	0%	-24%	29%	90%	86%
	Walk	1.6	0.0	21.4	4.6	258	421	-4%	-	-4%	-1%	-40%	-43%
	Cycle	2.6	0.0	25.9	5.9	65	166	-3%	-	-2%	-1%	-43%	-44%
	Metro/rail	19.8	263.9	62.8	18.9	229	4,530	-4%	-2%	-17%	15%	55%	49%

Appendix 6 Scenario-test summary tables: medium-term

Table A6.1. Summary by travel demand segment and mode: rS01 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	***All***	***10.6***	***465.3***	***44.7***	***14.2***	***1,992***	***21,109***	***-4%***	***15%***	***1%***	***-5%***	***0%***	***-4%***
	Car	11.1	762.8	41.6	16.1	1,003	11,174	-11%	27%	-3%	-9%	-11%	-21%
	Bus	5.7	100.6	42.3	8.1	381	2,165	4%	0%	2%	2%	11%	15%
	Walk	1.4	0.0	18.3	4.5	178	244	1%	-	1%	0%	6%	7%
	Cycle	2.7	0.0	26.7	6.0	67	181	2%	-	1%	1%	8%	10%
	Metro/rail	20.3	341.1	72.3	16.8	362	7,345	6%	3%	2%	4%	24%	32%
2	***All***	***8.9***	***254.5***	***43.9***	***12.1***	***6,524***	***57,941***	***-3%***	***-4%***	***3%***	***-6%***	***0%***	***-3%***
	Car	6.6	437.6	37.8	10.5	2,525	16,764	-27%	8%	-6%	-22%	-22%	-43%
	Bus	6.3	100.6	43.3	8.7	1,725	10,826	5%	0%	2%	3%	20%	26%
	Walk	1.4	0.0	18.6	4.5	766	1,064	2%	-	1%	0%	12%	14%
	Cycle	2.6	0.0	26.1	5.9	333	862	2%	-	1%	1%	15%	17%
	Metro/rail	24.2	324.8	79.5	18.2	1,176	28,425	4%	5%	2%	2%	37%	42%
3	***All***	***8.4***	***156.5***	***43.4***	***11.7***	***2,749***	***23,227***	***1%***	***-9%***	***3%***	***-2%***	***0%***	***1%***
	Car	4.3	271.1	34.9	7.3	762	3,243	-32%	4%	-7%	-28%	-33%	-55%
	Bus	7.2	100.7	45.3	9.5	927	6,635	4%	0%	2%	2%	26%	31%
	Walk	1.4	0.0	19.1	4.5	433	623	3%	-	2%	0%	18%	21%
	Cycle	2.7	0.0	26.6	6.1	189	508	3%	-	2%	1%	22%	26%
	Metro/rail	28.0	298.0	85.8	19.6	437	12,217	-2%	4%	0%	-2%	26%	24%
4	***All***	***6.0***	***243.9***	***38.5***	***9.4***	***331***	***1,985***	***-8%***	***9%***	***-1%***	***-7%***	***0%***	***-8%***
	Car	6.5	456.2	38.7	10.1	136	888	-16%	21%	-3%	-13%	-10%	-24%
	Bus	5.4	100.5	40.7	7.9	103	553	1%	0%	0%	1%	10%	11%
	Walk	1.3	0.0	18.1	4.5	46	62	1%	-	0%	0%	7%	7%
	Cycle	2.4	0.0	25.2	5.7	17	41	1%	-	0%	0%	7%	8%
	Metro/rail	15.3	287.1	69.8	13.1	29	441	2%	1%	1%	1%	10%	13%
5	***All***	***5.3***	***160.2***	***37.4***	***8.5***	***1,922***	***10,187***	***-6%***	***-1%***	***-1%***	***-6%***	***0%***	***-6%***
	Car	4.7	314.8	36.5	7.7	621	2,897	-22%	15%	-4%	-18%	-20%	-38%
	Bus	5.7	100.6	41.6	8.3	710	4,070	1%	0%	0%	1%	15%	16%
	Walk	1.4	0.0	18.4	4.5	308	423	1%	-	1%	0%	10%	12%
	Cycle	2.5	0.0	25.6	5.8	134	333	1%	-	1%	0%	12%	13%
	Metro/rail	16.5	274.5	71.1	13.9	149	2,464	2%	1%	1%	1%	17%	19%
6	***All***	***4.9***	***106.5***	***36.3***	***8.1***	***351***	***1,719***	***-2%***	***-6%***	***0%***	***-2%***	***0%***	***-3%***
	Car	3.4	219.3	34.2	5.9	78	264	-24%	12%	-5%	-20%	-33%	-49%
	Bus	6.3	100.6	42.9	8.8	151	946	-1%	0%	0%	0%	17%	17%
	Walk	1.4	0.0	19.0	4.5	72	102	2%	-	2%	0%	14%	16%
	Cycle	2.6	0.0	26.0	6.0	31	80	1%	-	1%	1%	16%	18%
	Metro/rail	16.7	258.3	72.8	13.8	20	327	0%	1%	0%	0%	19%	18%
7	***All***	***33.6***	***1809.4***	***57.0***	***35.4***	***53***	***1,794***	***-1%***	***36%***	***-3%***	***2%***	***0%***	***-1%***
	Car	33.9	2104.2	57.6	35.3	35	1,200	-21%	20%	-10%	-12%	-5%	-25%
	Bus	5.6	100.6	42.8	7.9	5	30	2%	0%	1%	1%	6%	9%
	Walk	1.6	0.0	20.8	4.5	4	7	0%	-	0%	0%	5%	5%
	Cycle	3.1	0.0	29.2	6.4	1	4	1%	-	0%	0%	5%	6%
	Metro/rail	79.1	3091.1	92.5	51.3	7	553	144%	217%	24%	97%	22%	198%
8	***All***	***13.6***	***698.0***	***46.2***	***17.7***	***223***	***3,038***	***-16%***	***8%***	***-2%***	***-14%***	***0%***	***-16%***
	Car	14.3	944.8	44.3	19.3	151	2,149	-21%	16%	-6%	-16%	-8%	-27%
	Bus	6.6	100.7	44.7	8.8	23	151	7%	0%	2%	4%	20%	28%
	Walk	1.6	0.0	20.7	4.5	17	27	1%	-	1%	0%	14%	15%
	Cycle	2.8	0.0	27.3	6.1	5	14	1%	-	1%	1%	15%	17%
	Metro/rail	25.6	408.9	77.6	19.8	27	696	8%	2%	4%	4%	26%	37%
9	***All***	***10.4***	***446.7***	***44.5***	***14.0***	***65***	***671***	***-17%***	***-4%***	***-1%***	***-16%***	***0%***	***-17%***
	Car	9.5	624.1	40.7	14.0	40	381	-29%	6%	-7%	-24%	-15%	-39%
	Bus	7.9	100.8	47.1	10.0	9	69	12%	0%	4%	8%	39%	55%
	Walk	1.6	0.0	20.9	4.6	6	9	1%	-	1%	0%	25%	26%
	Cycle	2.8	0.0	27.1	6.1	2	4	2%	-	1%	1%	27%	30%
	Metro/rail	24.9	357.6	79.8	18.7	8	208	10%	4%	5%	5%	48%	62%
10	***All***	***9.6***	***320.0***	***42.8***	***13.5***	***2,029***	***19,501***	***-12%***	***11%***	***-1%***	***-11%***	***0%***	***-12%***
	Car	12.0	652.3	42.0	17.2	751	9,047	-20%	29%	-5%	-16%	-15%	-32%
	Bus	5.9	100.6	42.3	8.4	556	3,283	2%	0%	1%	1%	11%	14%
	Walk	1.6	0.0	21.2	4.6	334	538	0%	-	0%	0%	9%	9%
	Cycle	2.6	0.0	26.3	6.0	87	227	1%	-	0%	0%	9%	10%
	Metro/rail	21.3	344.2	74.5	17.2	301	6,406	5%	1%	2%	3%	17%	22%
11	***All***	***8.6***	***203.1***	***42.1***	***12.2***	***10,026***	***86,183***	***-17%***	***-2%***	***0%***	***-16%***	***0%***	***-17%***
	Car	9.0	415.7	39.4	13.7	3,058	27,468	-35%	19%	-9%	-29%	-29%	-54%
	Bus	6.5	100.6	43.5	8.9	3,115	20,111	5%	0%	2%	3%	21%	27%
	Walk	1.7	0.0	21.8	4.6	1,903	3,165	1%	-	1%	0%	16%	17%
	Cycle	2.6	0.0	26.3	6.0	551	1,445	1%	-	1%	1%	17%	19%
	Metro/rail	24.3	322.5	78.7	18.5	1,399	33,994	7%	4%	4%	3%	36%	45%
12	***All***	***6.9***	***125.3***	***40.1***	***10.4***	***2,155***	***14,917***	***-17%***	***-11%***	***1%***	***-18%***	***0%***	***-18%***
	Car	6.0	252.1	36.6	9.8	504	3,027	-47%	9%	-12%	-40%	-44%	-71%
	Bus	7.1	100.7	45.1	9.5	740	5,282	6%	0%	2%	4%	32%	40%
	Walk	1.7	0.0	22.6	4.6	531	920	2%	-	1%	0%	23%	25%
	Cycle	2.7	0.0	26.6	6.1	143	385	2%	-	1%	1%	26%	29%
	Metro/rail	22.4	289.1	78.9	17.0	237	5,302	8%	7%	4%	4%	61%	74%

Table A6.2. Summary by travel demand segment and mode: rS02 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.1*	*379.1*	*44.3*	*15.0*	*1,992*	*22,032*	*0%*	*-7%*	*0%*	*0%*	*0%*	*0%*
	Car	12.7	608.3	43.0	17.8	1,089	13,872	1%	1%	0%	1%	-3%	-2%
	Bus	5.4	0.0	41.5	7.8	390	2,112	-1%	-100%	0%	0%	13%	13%
	Walk	1.4	0.0	18.2	4.5	161	218	0%	-	0%	0%	-4%	-4%
	Cycle	2.6	0.0	26.4	6.0	60	159	0%	-	0%	0%	-4%	-4%
	Metro/rail	19.5	317.5	70.9	16.5	291	5,671	2%	-4%	0%	2%	0%	2%
2	*All*	*9.2*	*227.4*	*43.1*	*12.9*	*6,524*	*60,239*	*1%*	*-14%*	*1%*	*0%*	*0%*	*1%*
	Car	9.4	416.7	40.4	14.0	2,933	27,576	3%	3%	0%	3%	-10%	-7%
	Bus	5.9	0.0	42.1	8.3	1,864	10,907	-2%	-100%	-1%	-1%	29%	27%
	Walk	1.4	0.0	18.2	4.5	617	839	-1%	-	-1%	0%	-10%	-10%
	Cycle	2.5	0.0	25.8	5.9	260	658	0%	-	0%	0%	-10%	-11%
	Metro/rail	23.8	307.1	77.9	18.4	850	20,259	3%	-1%	0%	3%	-1%	1%
3	*All*	*8.7*	*123.1*	*43.4*	*12.0*	*2,749*	*23,822*	*3%*	*-28%*	*3%*	*1%*	*0%*	*3%*
	Car	6.7	275.7	37.4	10.8	879	5,926	7%	6%	0%	7%	-23%	-18%
	Bus	6.6	0.0	43.9	9.0	1,135	7,520	-4%	-100%	-1%	-2%	54%	48%
	Walk	1.4	0.0	18.5	4.5	288	397	-2%	-	-1%	0%	-22%	-23%
	Cycle	2.6	0.0	26.1	6.0	118	307	0%	-	0%	0%	-24%	-24%
	Metro/rail	29.5	292.4	86.0	20.6	328	9,673	3%	2%	0%	3%	-5%	-2%
4	*All*	*6.5*	*186.9*	*38.9*	*10.1*	*331*	*2,158*	*0%*	*-17%*	*0%*	*0%*	*0%*	*0%*
	Car	7.8	380.8	39.9	11.8	144	1,123	1%	1%	0%	1%	-5%	-4%
	Bus	5.3	0.0	40.4	7.8	105	555	-1%	-100%	0%	0%	12%	12%
	Walk	1.3	0.0	18.0	4.4	41	55	0%	-	0%	0%	-5%	-5%
	Cycle	2.4	0.0	25.1	5.7	15	36	0%	-	0%	0%	-5%	-5%
	Metro/rail	15.2	279.5	69.4	13.2	25	388	2%	-2%	0%	2%	-3%	-1%
5	*All*	*5.7*	*114.1*	*38.0*	*9.0*	*1,922*	*10,984*	*1%*	*-29%*	*1%*	*0%*	*0%*	*1%*
	Car	6.1	277.5	38.0	9.6	675	4,092	2%	1%	0%	2%	-13%	-12%
	Bus	5.6	0.0	41.1	8.1	778	4,328	-2%	-100%	-1%	-1%	26%	24%
	Walk	1.3	0.0	18.1	4.5	247	333	-1%	-	-1%	0%	-11%	-12%
	Cycle	2.4	0.0	25.3	5.8	104	256	-1%	-	0%	0%	-13%	-13%
	Metro/rail	16.7	271.2	70.4	14.2	118	1,975	4%	0%	0%	4%	-8%	-4%
6	*All*	*5.3*	*56.7*	*37.8*	*8.4*	*351*	*1,862*	*6%*	*-50%*	*4%*	*2%*	*0%*	*6%*
	Car	4.5	196.6	35.8	7.6	83	377	1%	1%	-1%	2%	-29%	-28%
	Bus	6.0	0.0	42.3	8.6	188	1,132	-4%	-100%	-2%	-3%	46%	40%
	Walk	1.4	0.0	18.3	4.5	47	65	-2%	-	-2%	0%	-25%	-27%
	Cycle	2.5	0.0	25.7	5.9	19	49	-2%	-	-1%	-1%	-27%	-29%
	Metro/rail	17.5	260.9	72.6	14.5	14	240	5%	2%	0%	5%	-17%	-13%
7	*All*	*33.9*	*1321.9*	*58.9*	*34.6*	*54*	*1,816*	*0%*	*-1%*	*0%*	*0%*	*0%*	*0%*
	Car	42.9	1758.5	64.0	40.2	37	1,591	1%	0%	0%	0%	-1%	0%
	Bus	5.5	0.0	42.4	7.7	5	29	-1%	-100%	0%	0%	6%	5%
	Walk	1.6	0.0	20.8	4.5	4	7	0%	-	0%	0%	-1%	-1%
	Cycle	3.1	0.0	29.1	6.4	1	3	0%	-	0%	0%	-1%	-1%
	Metro/rail	32.5	958.5	74.6	26.2	6	186	0%	-2%	0%	0%	0%	0%
8	*All*	*16.1*	*628.0*	*47.3*	*20.5*	*224*	*3,609*	*0%*	*-2%*	*0%*	*0%*	*0%*	*0%*
	Car	18.2	820.4	47.1	23.1	161	2,923	1%	1%	0%	0%	-2%	-1%
	Bus	6.1	0.0	43.6	8.4	22	133	-1%	-100%	-1%	-1%	14%	13%
	Walk	1.6	0.0	20.6	4.5	15	23	0%	-	0%	0%	-2%	-2%
	Cycle	2.8	0.0	27.1	6.1	4	12	0%	-	0%	0%	-2%	-2%
	Metro/rail	23.8	388.7	74.8	19.1	22	518	1%	-3%	0%	1%	1%	2%
9	*All*	*12.5*	*444.4*	*44.9*	*16.7*	*65*	*811*	*0%*	*-5%*	*0%*	*0%*	*0%*	*0%*
	Car	13.5	595.5	43.9	18.5	45	612	1%	1%	0%	1%	-4%	-3%
	Bus	6.9	0.0	44.9	9.2	8	57	-2%	-100%	-1%	-1%	31%	28%
	Walk	1.6	0.0	20.6	4.5	5	7	0%	-	0%	0%	-4%	-4%
	Cycle	2.7	0.0	26.8	6.0	1	3	0%	-	0%	0%	-4%	-4%
	Metro/rail	23.2	336.7	76.1	18.3	6	132	2%	-2%	0%	2%	1%	3%
10	*All*	*10.9*	*254.4*	*43.2*	*15.1*	*2,026*	*22,064*	*0%*	*-12%*	*0%*	*-1%*	*0%*	*0%*
	Car	15.3	511.5	44.4	20.7	845	12,959	2%	1%	0%	1%	-4%	-3%
	Bus	5.7	0.0	41.9	8.2	559	3,201	-1%	-100%	0%	0%	12%	11%
	Walk	1.6	0.0	21.1	4.6	293	468	0%	-	0%	0%	-5%	-5%
	Cycle	2.6	0.0	26.2	5.9	76	196	0%	-	0%	0%	-5%	-5%
	Metro/rail	20.6	327.4	73.0	16.9	254	5,240	1%	-4%	0%	1%	-1%	0%
11	*All*	*10.2*	*170.5*	*42.5*	*14.4*	*10,037*	*102,702*	*-1%*	*-18%*	*1%*	*-1%*	*0%*	*-1%*
	Car	14.4	361.3	43.6	19.9	3,891	56,216	4%	3%	0%	3%	-10%	-6%
	Bus	6.1	0.0	42.6	8.5	3,268	19,821	-2%	-100%	-1%	-1%	27%	25%
	Walk	1.6	0.0	21.4	4.6	1,468	2,397	-1%	-	-1%	0%	-11%	-12%
	Cycle	2.6	0.0	26.1	5.9	417	1,074	0%	-	0%	0%	-12%	-12%
	Metro/rail	23.3	307.4	76.0	18.4	994	23,193	2%	-1%	0%	2%	-3%	-1%
12	*All*	*8.4*	*100.1*	*40.8*	*12.4*	*2,158*	*18,201*	*1%*	*-29%*	*2%*	*-2%*	*0%*	*0%*
	Car	12.2	247.1	41.6	17.6	723	8,856	8%	7%	1%	7%	-20%	-14%
	Bus	6.5	0.0	43.4	8.9	875	5,655	-4%	-100%	-1%	-2%	56%	50%
	Walk	1.7	0.0	21.9	4.6	337	564	-2%	-	-2%	0%	-22%	-23%
	Cycle	2.6	0.0	26.2	6.0	87	228	-1%	-	0%	0%	-23%	-24%
	Metro/rail	21.4	275.7	75.6	17.0	135	2,897	4%	2%	0%	4%	-8%	-5%

Table A6.3. Summary by travel demand segment and mode: rS03 vs Reference Case

Flow	Mode	Scenario tests						Percentage changes from reference case					
		Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*10.9*	*493.7*	*42.4*	*15.4*	*1,992*	*21,699*	*-1%*	*22%*	*-4%*	*3%*	*0%*	*-1%*
	Car	13.4	640.4	43.6	18.4	1,235	16,526	6%	6%	1%	5%	10%	17%
	Bus	5.6	100.6	42.1	8.0	357	1,999	3%	0%	1%	1%	4%	6%
	Walk	1.4	0.0	18.3	4.5	171	234	1%	-	1%	0%	2%	3%
	Cycle	2.7	0.0	26.7	6.0	65	173	2%	-	1%	1%	3%	5%
	Metro/rail	16.9	956.6	65.3	15.5	164	2,767	-12%	189%	-8%	-4%	-44%	-50%
2	*All*	*8.9*	*344.2*	*39.9*	*13.4*	*6,525*	*58,231*	*-3%*	*30%*	*-7%*	*4%*	*0%*	*-3%*
	Car	11.3	499.4	42.0	16.2	3,774	42,699	24%	23%	4%	19%	16%	44%
	Bus	6.5	100.6	43.8	8.8	1,523	9,821	8%	0%	3%	5%	6%	15%
	Walk	1.4	0.0	18.5	4.5	700	965	1%	-	1%	0%	3%	3%
	Cycle	2.6	0.0	26.1	5.9	300	778	2%	-	1%	1%	3%	6%
	Metro/rail	17.3	911.5	64.5	16.1	229	3,968	-25%	194%	-17%	-10%	-73%	-80%
3	*All*	*8.2*	*218.3*	*40.4*	*12.2*	*2,749*	*22,654*	*-2%*	*27%*	*-4%*	*3%*	*0%*	*-2%*
	Car	9.2	367.1	39.5	13.9	1,338	12,271	46%	41%	6%	38%	17%	71%
	Bus	10.5	101.0	53.0	11.9	852	8,926	52%	0%	19%	28%	16%	76%
	Walk	1.4	0.0	18.8	4.5	373	527	1%	-	1%	0%	1%	2%
	Cycle	2.7	0.0	26.7	6.1	159	430	3%	-	2%	2%	3%	6%
	Metro/rail	19.1	867.5	64.5	17.8	26	500	-33%	203%	-25%	-11%	-92%	-95%
4	*All*	*6.2*	*246.8*	*37.5*	*9.9*	*331*	*2,038*	*-6%*	*10%*	*-3%*	*-2%*	*0%*	*-6%*
	Car	7.9	384.1	40.0	11.8	158	1,246	2%	2%	0%	2%	4%	6%
	Bus	5.3	100.5	40.5	7.9	97	517	0%	0%	0%	0%	4%	4%
	Walk	1.3	0.0	18.0	4.4	45	60	0%	-	0%	0%	3%	3%
	Cycle	2.4	0.0	25.2	5.7	16	39	0%	-	0%	0%	3%	4%
	Metro/rail	12.3	778.4	64.3	11.5	14	175	-18%	173%	-7%	-11%	-46%	-55%
5	*All*	*5.1*	*168.6*	*35.9*	*8.6*	*1,921*	*9,889*	*-9%*	*4%*	*-5%*	*-5%*	*0%*	*-9%*
	Car	6.2	285.4	38.3	9.8	827	5,154	4%	4%	0%	4%	6%	11%
	Bus	5.7	100.6	41.5	8.2	646	3,682	1%	0%	0%	0%	5%	5%
	Walk	1.4	0.0	18.3	4.5	290	395	0%	-	0%	0%	4%	4%
	Cycle	2.5	0.0	25.5	5.8	125	309	0%	-	0%	0%	4%	5%
	Metro/rail	10.6	692.7	59.9	10.6	33	350	-35%	156%	-15%	-23%	-74%	-83%
6	*All*	*4.6*	*112.4*	*34.9*	*7.9*	*351*	*1,608*	*-9%*	*-1%*	*-4%*	*-5%*	*0%*	*-9%*
	Car	4.7	204.6	36.2	7.8	123	581	6%	5%	0%	5%	6%	11%
	Bus	6.4	100.6	43.2	8.8	134	853	1%	0%	1%	1%	4%	5%
	Walk	1.4	0.0	18.8	4.5	65	92	0%	-	0%	0%	4%	4%
	Cycle	2.6	0.0	26.0	5.9	28	71	1%	-	0%	0%	4%	5%
	Metro/rail	8.9	618.1	55.5	9.7	1	11	-46%	142%	-24%	-30%	-92%	-96%
7	*All*	*33.8*	*1401.2*	*58.1*	*34.9*	*54*	*1,808*	*0%*	*5%*	*-1%*	*1%*	*0%*	*0%*
	Car	42.3	1738.5	63.6	39.9	38	1,618	-1%	-1%	0%	0%	2%	2%
	Bus	5.5	100.6	42.6	7.8	5	29	0%	0%	0%	0%	2%	3%
	Walk	1.6	0.0	20.8	4.5	4	7	0%	-	0%	0%	2%	2%
	Cycle	3.1	0.0	29.1	6.4	1	3	0%	-	0%	0%	2%	2%
	Metro/rail	32.9	1726.3	71.8	27.5	5	152	1%	77%	-4%	5%	-19%	-18%
8	*All*	*15.8*	*700.2*	*45.7*	*20.7*	*224*	*3,534*	*-2%*	*9%*	*-3%*	*1%*	*0%*	*-2%*
	Car	18.3	826.9	47.2	23.2	172	3,141	1%	1%	0%	1%	5%	6%
	Bus	6.2	100.6	44.0	8.5	20	124	1%	0%	0%	0%	4%	5%
	Walk	1.6	0.0	20.7	4.5	16	24	0%	-	0%	0%	3%	3%
	Cycle	2.8	0.0	27.2	6.1	5	13	1%	-	0%	0%	4%	4%
	Metro/rail	19.4	1059.1	66.9	17.4	12	232	-18%	163%	-10%	-8%	-45%	-54%
9	*All*	*12.0*	*504.8*	*42.6*	*16.9*	*65*	*779*	*-4%*	*8%*	*-5%*	*1%*	*0%*	*-4%*
	Car	13.8	607.7	44.1	18.7	50	694	3%	3%	1%	2%	7%	10%
	Bus	7.2	100.7	45.7	9.4	7	48	2%	0%	1%	1%	5%	7%
	Walk	1.6	0.0	20.7	4.5	5	8	0%	-	0%	0%	4%	4%
	Cycle	2.7	0.0	27.0	6.1	1	3	1%	-	1%	1%	5%	6%
	Metro/rail	15.9	904.3	62.6	15.2	2	26	-30%	164%	-18%	-15%	-71%	-80%
10	*All*	*10.3*	*334.3*	*40.9*	*15.1*	*2,025*	*20,881*	*-6%*	*16%*	*-5%*	*0%*	*0%*	*-6%*
	Car	15.5	519.3	44.6	20.9	957	14,874	3%	3%	1%	2%	8%	12%
	Bus	5.8	100.6	42.1	8.3	527	3,062	1%	0%	0%	0%	5%	6%
	Walk	1.6	0.0	21.2	4.6	322	518	0%	-	0%	0%	5%	5%
	Cycle	2.6	0.0	26.3	6.0	84	218	1%	-	0%	0%	5%	6%
	Metro/rail	16.3	934.3	65.7	14.9	136	2,210	-20%	174%	-10%	-11%	-47%	-58%
11	*All*	*9.5*	*223.2*	*39.3*	*14.4*	*10,017*	*94,804*	*-8%*	*7%*	*-7%*	*-1%*	*0%*	*-8%*
	Car	14.7	368.7	43.9	20.0	4,813	70,550	5%	5%	1%	4%	11%	17%
	Bus	6.2	100.6	43.1	8.7	2,733	17,010	1%	0%	0%	0%	6%	7%
	Walk	1.7	0.0	21.7	4.6	1,736	2,869	0%	-	0%	0%	5%	6%
	Cycle	2.6	0.0	26.2	6.0	500	1,305	1%	-	1%	0%	6%	7%
	Metro/rail	13.0	790.5	60.1	13.0	235	3,069	-43%	156%	-21%	-28%	-77%	-87%
12	*All*	*7.9*	*142.8*	*37.6*	*12.6*	*2,160*	*17,070*	*-6%*	*1%*	*-5%*	*0%*	*0%*	*-6%*
	Car	12.0	244.2	41.8	17.2	997	11,912	6%	6%	1%	5%	10%	16%
	Bus	6.8	100.7	44.3	9.2	587	3,985	1%	0%	1%	1%	5%	6%
	Walk	1.7	0.0	22.3	4.6	448	766	0%	-	0%	0%	4%	4%
	Cycle	2.7	0.0	26.4	6.0	119	315	1%	-	1%	0%	5%	6%
	Metro/rail	9.7	644.8	53.9	10.7	9	91	-53%	139%	-29%	-34%	-94%	-97%

Table A6.4. Summary by travel demand segment and mode: rS04 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.0*	*390.3*	*45.3*	*14.6*	*1,992*	*21,990*	*0%*	*-4%*	*2%*	*-2%*	*0%*	*0%*
	Car	13.0	615.9	44.9	17.4	1,025	13,312	3%	2%	4%	-1%	-9%	-6%
	Bus	5.4	100.5	41.4	7.8	388	2,102	-1%	0%	0%	-1%	13%	12%
	Walk	1.4	0.0	18.4	4.5	185	253	1%	-	1%	0%	10%	11%
	Cycle	2.6	0.0	26.4	6.0	70	185	0%	-	0%	0%	11%	12%
	Metro/rail	19.0	329.8	70.7	16.1	323	6,138	-1%	0%	0%	-1%	11%	10%
2	*All*	*9.2*	*253.6*	*43.4*	*12.7*	*6,524*	*59,776*	*0%*	*-4%*	*2%*	*-2%*	*0%*	*0%*
	Car	9.3	410.1	41.5	13.4	2,945	27,327	2%	1%	3%	-1%	-9%	-8%
	Bus	5.9	100.6	42.2	8.3	1,588	9,322	-1%	0%	0%	-1%	10%	9%
	Walk	1.4	0.0	18.5	4.5	742	1,023	1%	-	1%	0%	9%	10%
	Cycle	2.5	0.0	25.9	5.9	320	813	0%	-	0%	0%	10%	10%
	Metro/rail	22.9	308.8	77.6	17.7	930	21,291	-1%	0%	0%	-1%	8%	7%
3	*All*	*8.4*	*167.4*	*42.5*	*11.8*	*2,749*	*23,079*	*0%*	*-2%*	*1%*	*-1%*	*0%*	*0%*
	Car	6.3	260.4	37.9	10.0	1,078	6,805	0%	0%	1%	-1%	-6%	-5%
	Bus	6.8	100.7	44.4	9.2	768	5,232	-1%	0%	0%	-1%	4%	3%
	Walk	1.4	0.0	18.8	4.5	383	539	0%	-	0%	0%	4%	5%
	Cycle	2.6	0.0	26.2	6.0	162	425	0%	-	0%	0%	5%	5%
	Metro/rail	28.2	285.6	85.3	19.8	358	10,078	-1%	0%	-1%	-1%	3%	2%
4	*All*	*6.5*	*217.0*	*39.2*	*10.0*	*331*	*2,154*	*0%*	*-3%*	*1%*	*-1%*	*0%*	*0%*
	Car	7.9	385.6	40.8	11.7	139	1,106	3%	2%	2%	0%	-8%	-6%
	Bus	5.3	100.5	40.4	7.8	101	529	-1%	0%	0%	-1%	7%	6%
	Walk	1.3	0.0	18.1	4.5	46	62	1%	-	1%	0%	6%	7%
	Cycle	2.4	0.0	25.2	5.7	17	41	0%	-	0%	0%	7%	7%
	Metro/rail	14.7	283.0	69.1	12.8	28	416	-1%	-1%	0%	-1%	8%	6%
5	*All*	*5.7*	*157.3*	*37.8*	*9.0*	*1,923*	*10,875*	*0%*	*-3%*	*0%*	*-1%*	*0%*	*0%*
	Car	6.0	276.7	38.6	9.4	728	4,398	1%	1%	1%	0%	-7%	-5%
	Bus	5.6	100.6	41.3	8.2	645	3,629	-1%	0%	0%	0%	4%	4%
	Walk	1.4	0.0	18.3	4.5	290	396	0%	-	0%	0%	4%	5%
	Cycle	2.5	0.0	25.5	5.8	125	309	0%	-	0%	0%	5%	5%
	Metro/rail	15.9	269.2	70.2	13.6	135	2,143	-1%	-1%	0%	-1%	5%	4%
6	*All*	*5.0*	*111.7*	*36.5*	*8.2*	*351*	*1,763*	*0%*	*-2%*	*0%*	*0%*	*0%*	*0%*
	Car	4.5	195.5	36.3	7.4	111	497	0%	0%	1%	0%	-5%	-5%
	Bus	6.3	100.6	42.9	8.8	132	824	-1%	0%	0%	0%	2%	2%
	Walk	1.4	0.0	18.8	4.5	64	91	0%	-	0%	0%	2%	3%
	Cycle	2.6	0.0	25.9	5.9	27	70	0%	-	0%	0%	3%	3%
	Metro/rail	16.6	254.0	72.5	13.7	17	282	-1%	0%	0%	-1%	3%	2%
7	*All*	*33.9*	*1325.8*	*61.1*	*33.3*	*53*	*1,814*	*0%*	*-1%*	*4%*	*-4%*	*0%*	*0%*
	Car	44.3	1810.9	68.3	38.9	36	1,577	4%	3%	7%	-3%	-5%	-1%
	Bus	5.4	100.5	42.1	7.7	6	31	-2%	0%	-1%	-1%	14%	12%
	Walk	1.6	0.0	20.9	4.5	5	8	0%	-	0%	0%	11%	11%
	Cycle	3.1	0.0	28.9	6.4	1	4	-1%	-	-1%	0%	11%	10%
	Metro/rail	31.6	949.4	74.2	25.6	6	194	-3%	-3%	0%	-2%	7%	5%
8	*All*	*16.1*	*632.3*	*49.2*	*19.6*	*223*	*3,593*	*0%*	*-2%*	*4%*	*-4%*	*0%*	*-1%*
	Car	18.4	830.5	50.1	22.1	156	2,884	2%	2%	6%	-4%	-4%	-2%
	Bus	6.0	100.6	43.4	8.3	22	132	-2%	0%	-1%	-1%	14%	11%
	Walk	1.6	0.0	20.7	4.5	17	27	1%	-	1%	0%	12%	13%
	Cycle	2.7	0.0	27.1	6.1	5	14	0%	-	0%	0%	13%	12%
	Metro/rail	23.0	395.8	74.2	18.6	23	537	-2%	-2%	-1%	-2%	8%	5%
9	*All*	*12.5*	*458.8*	*46.2*	*16.2*	*65*	*810*	*0%*	*-2%*	*3%*	*-3%*	*0%*	*0%*
	Car	13.6	596.9	45.9	17.7	45	615	2%	1%	5%	-3%	-4%	-2%
	Bus	6.9	100.7	44.9	9.2	7	48	-3%	0%	-1%	-2%	11%	8%
	Walk	1.6	0.0	20.8	4.5	5	8	1%	-	1%	0%	10%	11%
	Cycle	2.7	0.0	26.8	6.0	1	4	0%	-	0%	0%	11%	11%
	Metro/rail	22.2	338.9	75.5	17.7	6	135	-2%	-1%	-1%	-1%	8%	5%
10	*All*	*10.9*	*280.7*	*43.5*	*15.0*	*2,026*	*22,041*	*-1%*	*-3%*	*1%*	*-1%*	*0%*	*-1%*
	Car	15.6	518.4	45.4	20.7	816	12,765	4%	3%	2%	1%	-7%	-4%
	Bus	5.7	100.6	41.9	8.2	529	3,033	-1%	0%	0%	0%	6%	5%
	Walk	1.6	0.0	21.2	4.6	323	521	1%	-	0%	0%	5%	6%
	Cycle	2.6	0.0	26.3	5.9	84	218	0%	-	0%	0%	6%	6%
	Metro/rail	20.1	336.3	72.7	16.6	274	5,504	-1%	-2%	0%	-1%	6%	5%
11	*All*	*10.2*	*203.2*	*42.5*	*14.5*	*10,041*	*102,860*	*-1%*	*-2%*	*1%*	*-1%*	*0%*	*-1%*
	Car	14.4	359.0	44.3	19.5	3,973	57,254	4%	3%	2%	1%	-8%	-5%
	Bus	6.1	100.6	42.8	8.6	2,725	16,672	-1%	0%	0%	-1%	6%	5%
	Walk	1.7	0.0	21.7	4.6	1,735	2,875	1%	-	0%	0%	5%	6%
	Cycle	2.6	0.0	26.2	6.0	500	1,298	0%	-	0%	0%	6%	6%
	Metro/rail	22.3	306.5	75.4	17.8	1,109	24,762	-2%	-1%	-1%	-1%	8%	6%
12	*All*	*8.4*	*139.5*	*39.9*	*12.5*	*2,159*	*18,033*	*0%*	*-1%*	*0%*	*-1%*	*0%*	*0%*
	Car	11.5	232.5	41.8	16.5	865	9,913	1%	1%	1%	0%	-5%	-3%
	Bus	6.7	100.7	44.0	9.1	578	3,862	0%	0%	0%	0%	3%	3%
	Walk	1.7	0.0	22.3	4.6	443	758	0%	-	0%	0%	3%	3%
	Cycle	2.6	0.0	26.3	6.0	117	309	0%	-	0%	0%	3%	4%
	Metro/rail	20.4	268.8	75.3	16.3	156	3,192	-1%	0%	-1%	-1%	6%	5%

Table A6.5. Summary by travel demand segment and mode: rS05 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*10.9*	*374.3*	*41.2*	*15.9*	*1,992*	*21,783*	*-1%*	*-8%*	*-7%*	*6%*	*0%*	*-1%*
	Car	14.3	675.5	43.9	19.5	871	12,424	13%	12%	2%	11%	-23%	-12%
	Bus	5.7	100.6	31.8	10.7	702	3,978	4%	0%	-24%	36%	104%	112%
	Walk	1.3	0.0	17.9	4.5	119	160	-2%	-	-1%	0%	-29%	-30%
	Cycle	2.7	0.0	26.7	6.0	44	118	2%	-	1%	1%	-30%	-28%
	Metro/rail	20.0	338.9	71.5	16.8	255	5,104	4%	2%	1%	3%	-12%	-9%
2	*All*	*9.2*	*237.8*	*39.4*	*14.1*	*6,524*	*60,316*	*1%*	*-10%*	*-8%*	*9%*	*0%*	*1%*
	Car	10.6	462.3	41.0	15.5	2,218	23,429	16%	14%	2%	14%	-32%	-21%
	Bus	6.1	100.6	32.5	11.2	2,925	17,789	2%	0%	-23%	33%	103%	108%
	Walk	1.3	0.0	17.9	4.5	458	611	-2%	-	-2%	0%	-33%	-35%
	Cycle	2.5	0.0	25.8	5.9	188	475	0%	-	0%	0%	-35%	-35%
	Metro/rail	24.5	315.2	79.1	18.6	735	18,012	6%	2%	2%	4%	-15%	-10%
3	*All*	*8.8*	*153.8*	*39.1*	*13.5*	*2,749*	*24,172*	*5%*	*-10%*	*-8%*	*13%*	*0%*	*5%*
	Car	7.0	283.8	37.5	11.2	685	4,796	11%	9%	0%	11%	-40%	-33%
	Bus	7.1	100.7	34.7	12.2	1,461	10,323	3%	0%	-22%	32%	98%	104%
	Walk	1.4	0.0	18.2	4.5	229	310	-3%	-	-3%	0%	-38%	-40%
	Cycle	2.6	0.0	26.0	5.9	92	236	-1%	-	-1%	-1%	-41%	-42%
	Metro/rail	30.1	288.0	87.1	20.7	283	8,506	5%	1%	2%	4%	-18%	-14%
4	*All*	*6.3*	*191.3*	*34.1*	*11.2*	*331*	*2,101*	*-3%*	*-15%*	*-12%*	*11%*	*0%*	*-3%*
	Car	8.5	407.1	40.0	12.7	99	837	9%	8%	0%	9%	-35%	-29%
	Bus	5.2	100.5	30.1	10.3	173	897	-2%	0%	-26%	32%	84%	80%
	Walk	1.3	0.0	17.5	4.4	29	38	-3%	-	-3%	0%	-32%	-34%
	Cycle	2.4	0.0	24.9	5.7	10	24	-2%	-	-1%	-1%	-35%	-36%
	Metro/rail	15.9	295.9	69.7	13.7	19	304	6%	4%	1%	6%	-27%	-23%
5	*All*	*5.7*	*141.0*	*32.9*	*10.5*	*1,922*	*11,030*	*1%*	*-13%*	*-13%*	*16%*	*0%*	*1%*
	Car	6.4	290.0	37.9	10.2	458	2,940	8%	6%	0%	8%	-41%	-37%
	Bus	5.5	100.5	30.8	10.6	1,128	6,164	-4%	0%	-26%	30%	83%	76%
	Walk	1.3	0.0	17.7	4.4	176	230	-4%	-	-3%	0%	-37%	-39%
	Cycle	2.4	0.0	25.1	5.7	72	172	-2%	-	-1%	-1%	-40%	-42%
	Metro/rail	17.2	279.6	70.8	14.6	89	1,524	7%	3%	1%	6%	-31%	-26%
6	*All*	*5.5*	*108.0*	*32.2*	*10.2*	*351*	*1,922*	*9%*	*-5%*	*-12%*	*23%*	*0%*	*9%*
	Car	4.6	198.1	35.7	7.7	62	284	3%	1%	-1%	4%	-47%	-46%
	Bus	6.0	100.6	32.1	11.2	228	1,363	-5%	0%	-25%	27%	77%	68%
	Walk	1.3	0.0	18.0	4.5	37	49	-5%	-	-4%	-1%	-42%	-44%
	Cycle	2.5	0.0	25.5	5.8	15	36	-3%	-	-2%	-1%	-46%	-47%
	Metro/rail	17.6	258.7	72.9	14.5	11	191	5%	1%	0%	5%	-34%	-31%
7	*All*	*33.7*	*1312.0*	*57.1*	*35.5*	*53*	*1,804*	*-1%*	*-2%*	*-3%*	*2%*	*0%*	*-1%*
	Car	46.6	1902.2	66.6	42.0	33	1,562	9%	9%	4%	5%	-10%	-2%
	Bus	5.4	100.5	31.4	10.4	10	55	-1%	0%	-26%	34%	100%	97%
	Walk	1.6	0.0	20.8	4.5	4	6	0%	-	0%	0%	-15%	-14%
	Cycle	3.2	0.0	29.5	6.4	1	3	3%	-	1%	1%	-14%	-12%
	Metro/rail	33.9	1029.6	75.3	27.0	5	179	4%	5%	1%	3%	-7%	-3%
8	*All*	*15.8*	*609.4*	*45.5*	*20.8*	*224*	*3,529*	*-2%*	*-5%*	*-4%*	*2%*	*0%*	*-2%*
	Car	19.1	858.0	47.7	24.0	144	2,752	6%	5%	1%	4%	-12%	-7%
	Bus	6.2	100.6	33.2	11.3	43	267	1%	0%	-24%	34%	123%	126%
	Walk	1.6	0.0	20.6	4.5	13	20	0%	-	0%	0%	-15%	-16%
	Cycle	2.8	0.0	27.4	6.1	4	10	2%	-	1%	1%	-15%	-14%
	Metro/rail	24.0	407.8	75.1	19.2	20	479	2%	1%	1%	1%	-8%	-6%
9	*All*	*12.3*	*428.7*	*42.9*	*17.2*	*65*	*798*	*-2%*	*-8%*	*-4%*	*3%*	*0%*	*-2%*
	Car	14.1	619.2	44.2	19.2	40	560	6%	5%	1%	5%	-16%	-11%
	Bus	7.2	100.7	35.1	12.4	15	111	3%	0%	-23%	33%	141%	148%
	Walk	1.5	0.0	20.5	4.5	4	6	-1%	-	-1%	0%	-18%	-18%
	Cycle	2.7	0.0	26.9	6.1	1	3	1%	-	0%	0%	-18%	-17%
	Metro/rail	23.0	345.3	76.4	18.1	5	118	1%	1%	0%	1%	-10%	-8%
10	*All*	*10.4*	*258.5*	*38.9*	*16.0*	*2,025*	*21,022*	*-5%*	*-10%*	*-10%*	*5%*	*0%*	*-5%*
	Car	17.1	564.1	45.3	22.7	637	10,882	13%	12%	2%	11%	-28%	-18%
	Bus	5.8	100.6	31.7	10.9	922	5,303	0%	0%	-24%	32%	85%	84%
	Walk	1.6	0.0	20.6	4.5	208	324	-3%	-	-3%	0%	-32%	-34%
	Cycle	2.6	0.0	26.2	5.9	53	136	0%	-	0%	0%	-34%	-34%
	Metro/rail	21.3	348.3	73.5	17.4	206	4,376	4%	2%	1%	4%	-20%	-17%
11	*All*	*9.9*	*191.5*	*38.2*	*15.6*	*10,026*	*99,218*	*-4%*	*-8%*	*-10%*	*6%*	*0%*	*-4%*
	Car	16.0	396.2	44.3	21.7	2,955	47,362	15%	13%	2%	13%	-32%	-21%
	Bus	6.1	100.6	32.6	11.3	4,907	30,125	0%	0%	-24%	31%	91%	90%
	Walk	1.6	0.0	20.9	4.6	1,058	1,684	-3%	-	-3%	0%	-36%	-38%
	Cycle	2.6	0.0	26.0	5.9	294	753	-1%	-	-1%	0%	-38%	-38%
	Metro/rail	23.8	315.5	76.7	18.6	811	19,294	4%	2%	1%	4%	-21%	-18%
12	*All*	*8.4*	*137.6*	*36.4*	*13.9*	*2,158*	*18,185*	*0%*	*-3%*	*-8%*	*10%*	*0%*	*0%*
	Car	13.1	260.8	42.0	18.7	587	7,661	15%	13%	1%	14%	-35%	-25%
	Bus	6.7	100.7	33.7	11.9	1,121	7,460	-1%	0%	-24%	30%	100%	98%
	Walk	1.6	0.0	21.5	4.6	267	440	-4%	-	-3%	0%	-38%	-40%
	Cycle	2.6	0.0	26.1	6.0	68	177	-1%	-	-1%	-1%	-40%	-41%
	Metro/rail	21.4	272.3	76.1	16.9	114	2,447	3%	1%	1%	3%	-22%	-20%

Table A6.6. Summary by travel demand segment and mode: rS06 vs Reference Case

		Scenario tests						Percentage changes from reference case					
Flow	Mode	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)	Average distance	Average cost	Average time	Average speed	Trip volume (000)	Trip-km (000)
1	*All*	*11.0*	*337.7*	*40.9*	*16.1*	*1,992*	*21,808*	*-1%*	*-17%*	*-7%*	*7%*	*0%*	*-1%*
	Car	13.5	638.1	43.4	18.7	755	10,198	7%	6%	1%	6%	-33%	-28%
	Bus	5.5	100.5	31.2	10.6	651	3,579	1%	0%	-25%	34%	89%	91%
	Walk	1.3	0.0	17.7	4.5	114	149	-3%	-	-3%	0%	-32%	-34%
	Cycle	2.6	0.0	26.2	5.9	41	106	-2%	-	-1%	-1%	-35%	-36%
	Metro/rail	18.1	291.4	58.8	18.4	430	7,775	-6%	-12%	-17%	13%	48%	39%
2	*All*	*9.4*	*217.6*	*39.3*	*14.3*	*6,524*	*61,026*	*2%*	*-18%*	*-8%*	*11%*	*0%*	*2%*
	Car	9.4	414.9	40.2	14.1	1,951	18,434	4%	2%	0%	4%	-40%	-38%
	Bus	5.8	100.6	31.8	11.0	2,751	16,079	-2%	0%	-25%	31%	91%	88%
	Walk	1.3	0.0	17.8	4.5	440	579	-4%	-	-3%	0%	-36%	-38%
	Cycle	2.5	0.0	25.5	5.8	178	441	-3%	-	-1%	-1%	-39%	-40%
	Metro/rail	21.2	276.8	64.7	19.6	1,204	25,493	-9%	-11%	-17%	10%	40%	28%
3	*All*	*8.9*	*150.9*	*38.4*	*13.9*	*2,749*	*24,541*	*6%*	*-12%*	*-9%*	*17%*	*0%*	*6%*
	Car	6.2	254.5	37.0	10.1	628	3,897	-1%	-3%	-1%	0%	-45%	-46%
	Bus	6.6	100.7	33.4	11.8	1,387	9,101	-5%	0%	-25%	27%	88%	80%
	Walk	1.3	0.0	18.0	4.5	224	300	-4%	-	-4%	-1%	-39%	-42%
	Cycle	2.5	0.0	25.7	5.9	89	224	-3%	-	-2%	-2%	-43%	-45%
	Metro/rail	26.2	273.8	70.7	22.2	421	11,019	-8%	-4%	-18%	11%	22%	11%
4	*All*	*6.7*	*191.9*	*34.8*	*11.5*	*331*	*2,216*	*3%*	*-14%*	*-10%*	*14%*	*0%*	*3%*
	Car	8.4	402.8	40.0	12.6	92	770	8%	7%	0%	8%	-39%	-34%
	Bus	5.2	100.5	30.1	10.3	163	844	-2%	0%	-26%	32%	73%	69%
	Walk	1.3	0.0	17.4	4.4	28	36	-4%	-	-3%	0%	-36%	-38%
	Cycle	2.3	0.0	24.8	5.7	10	23	-2%	-	-1%	-1%	-39%	-40%
	Metro/rail	14.0	260.9	57.7	14.6	39	544	-6%	-9%	-17%	12%	48%	39%
5	*All*	*6.1*	*143.8*	*33.7*	*10.9*	*1,923*	*11,807*	*8%*	*-11%*	*-10%*	*21%*	*0%*	*8%*
	Car	6.2	282.0	37.8	9.9	427	2,660	4%	3%	-1%	5%	-45%	-43%
	Bus	5.5	100.5	30.8	10.6	1,069	5,832	-4%	0%	-26%	30%	73%	67%
	Walk	1.3	0.0	17.6	4.4	168	218	-4%	-	-4%	-1%	-40%	-43%
	Cycle	2.4	0.0	25.0	5.7	68	162	-3%	-	-2%	-1%	-43%	-45%
	Metro/rail	15.3	252.8	58.2	15.7	192	2,937	-5%	-7%	-17%	14%	50%	42%
6	*All*	*5.8*	*111.9*	*32.9*	*10.6*	*351*	*2,039*	*16%*	*-2%*	*-10%*	*28%*	*0%*	*16%*
	Car	4.4	191.8	35.6	7.5	59	259	-1%	-2%	-1%	0%	-50%	-50%
	Bus	6.0	100.6	32.0	11.2	219	1,306	-5%	0%	-25%	27%	70%	61%
	Walk	1.3	0.0	17.9	4.5	35	47	-5%	-	-4%	-1%	-44%	-47%
	Cycle	2.5	0.0	25.4	5.8	14	34	-3%	-	-2%	-2%	-48%	-50%
	Metro/rail	15.9	245.7	59.5	16.0	25	392	-5%	-4%	-18%	16%	49%	42%
7	*All*	*33.9*	*1294.0*	*56.9*	*35.7*	*54*	*1,813*	*0%*	*-3%*	*-3%*	*3%*	*0%*	*0%*
	Car	48.3	1964.0	67.8	42.7	32	1,531	13%	12%	6%	7%	-15%	-4%
	Bus	5.4	100.5	31.4	10.4	10	52	-1%	0%	-26%	34%	88%	85%
	Walk	1.6	0.0	20.7	4.5	3	5	-1%	-	0%	0%	-19%	-20%
	Cycle	3.1	0.0	29.3	6.4	1	3	1%	-	1%	1%	-19%	-18%
	Metro/rail	28.0	757.9	62.7	26.8	8	222	-14%	-22%	-16%	3%	39%	20%
8	*All*	*16.0*	*585.8*	*45.6*	*21.1*	*224*	*3,579*	*-1%*	*-9%*	*-4%*	*3%*	*0%*	*-1%*
	Car	19.1	858.3	47.8	24.0	135	2,576	6%	5%	1%	4%	-18%	-13%
	Bus	6.2	100.6	33.1	11.3	40	250	1%	0%	-25%	34%	110%	111%
	Walk	1.5	0.0	20.4	4.5	12	19	-1%	-	-1%	0%	-20%	-21%
	Cycle	2.8	0.0	27.1	6.1	3	10	0%	-	0%	0%	-20%	-20%
	Metro/rail	22.0	341.5	63.1	21.0	33	724	-7%	-15%	-16%	11%	52%	42%
9	*All*	*12.6*	*410.2*	*43.3*	*17.5*	*65*	*820*	*1%*	*-12%*	*-3%*	*4%*	*0%*	*1%*
	Car	13.9	609.8	44.2	19.0	37	512	4%	3%	1%	4%	-22%	-18%
	Bus	7.2	100.7	34.8	12.4	14	103	2%	0%	-23%	33%	128%	132%
	Walk	1.5	0.0	20.3	4.5	4	6	-2%	-	-1%	0%	-22%	-23%
	Cycle	2.7	0.0	26.6	6.0	1	3	-1%	-	-1%	0%	-23%	-23%
	Metro/rail	21.3	305.8	64.0	20.0	9	196	-6%	-11%	-16%	12%	62%	52%
10	*All*	*10.8*	*253.3*	*39.6*	*16.4*	*2,027*	*21,975*	*-1%*	*-12%*	*-8%*	*8%*	*0%*	*-1%*
	Car	17.0	559.0	45.2	22.5	569	9,660	12%	11%	2%	10%	-36%	-28%
	Bus	5.7	100.6	31.6	10.9	849	4,867	-1%	0%	-25%	32%	70%	69%
	Walk	1.5	0.0	20.4	4.5	193	299	-4%	-	-3%	0%	-37%	-39%
	Cycle	2.5	0.0	25.9	5.9	49	123	-2%	-	-1%	-1%	-39%	-40%
	Metro/rail	19.2	299.6	61.5	18.7	366	7,026	-6%	-12%	-16%	12%	42%	34%
11	*All*	*10.5*	*191.6*	*39.1*	*16.1*	*10,045*	*105,493*	*2%*	*-8%*	*-7%*	*10%*	*0%*	*2%*
	Car	15.7	386.8	44.1	21.3	2,629	41,219	13%	11%	2%	11%	-39%	-31%
	Bus	6.1	100.6	32.4	11.3	4,578	27,948	-1%	0%	-24%	31%	78%	76%
	Walk	1.6	0.0	20.8	4.6	994	1,572	-4%	-	-4%	-1%	-40%	-42%
	Cycle	2.5	0.0	25.8	5.9	274	691	-2%	-	-1%	-1%	-42%	-43%
	Metro/rail	21.7	284.8	63.7	20.4	1,570	34,063	-5%	-8%	-16%	14%	52%	45%
12	*All*	*8.9*	*140.8*	*37.1*	*14.3*	*2,158*	*19,145*	*6%*	*-1%*	*-7%*	*13%*	*0%*	*6%*
	Car	12.6	251.3	41.7	18.1	529	6,665	11%	9%	1%	10%	-42%	-35%
	Bus	6.6	100.7	33.5	11.8	1,065	7,027	-2%	0%	-24%	29%	90%	87%
	Walk	1.6	0.0	21.4	4.6	255	418	-4%	-	-3%	-1%	-41%	-43%
	Cycle	2.6	0.0	25.9	5.9	65	166	-3%	-	-1%	-1%	-43%	-45%
	Metro/rail	20.0	260.7	62.6	19.1	244	4,869	-3%	-3%	-17%	17%	66%	60%

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